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Contents

Introduction

This thesis consists of three essays which show that using industry-level information in macroeconomic models brings valuable insights, even to "big" aggregate questions. The three essays study dynamic stochastic general equilibrium models at the level of industries. The first essay examines the importance of industry-level evidence for testing various explanations of the vanishing cyclicality of productivity in the U.S. in the mid-1980s. The second essay studies the implications of a medium-sized New Keynesian industry-level model for the identification of sources of business cycles. The third essay focuses on the effects of fiscal policy shocks in a small open economy model. The unifying feature of the three essays is the presence of a highly disaggregated industry structure with more than seventy industries connected via the input-output network.

Industry evidence and the vanishing cyclicality of labor productivity Aggregate labor productivity used to be strongly procyclical in the United States, but the procyclicality has largely disappeared since the mid-1980s. The first essay explores the industry-level evidence in order to discriminate between existing explanations of the vanishing procyclicality of the labor productivity.

I document the change in the cyclical properties of productivity in the U.S. using industry-level data and focus on a particularly puzzling feature, namely that the correlations of the industry productivity with industry output and labor input remained on average much more stable before and after the mid-1980s compared to the aggregate correlations. In other words, there is little evidence for the vanishing cyclicality of labor productivity at the industry level.

I construct a simple industry-level RBC model that nests two leading explanations of the vanishing cyclicality of productivity that have been proposed in the literature. I show that the two explanations have qualitatively different predictions for the cyclical properties of industry-level variables. The mechanism based on a structural change in the composition of aggregate shocks is able to generate the vanishing cyclicality of productivity and simultaneously replicate the stability of industry-level moments across time. In contrast, the mechanism based on increased labor market flexibility is less successful in matching the industry-level evidence.

This essay was previously published as a working paper in Vienna Economic Papers series, see Molnárová (2020).

Technology, demand, and productivity: what an industry model tells us about business cycles This essay is joint work with Michael Reiter. We study the relative importance of demand and technology shocks in generating business cycle fluctuations, both at the aggregate level and at the level of individual industries. We construct a New Keynesian DSGE model that is highly disaggregated at the industry level with an input-output network structure. Measured productivity in the model fluctuates in response to both technology and demand shocks due to endogenous factor utilization. We estimate the model by the simulated method of moments using U.S. industry data from 1960 to 2005.

We find that the aggregate technology shock has zero variance. Exogenous shocks to technology are necessary for our model to fit the data, but these shocks are exclusively industry-specific, uncorrelated across industries. The bulk of the aggregate fluctuations, including those in aggregate measured productivity, are explained through shocks to aggregate demand. This shock structure is supported by a host of information from the disaggregate data. Our second finding is that about half of the decrease in the cyclicality of measured productivity in the U.S. after the mid-1980s can be explained by the reduction in the size of demand shocks, in line with the narrative of the *great moderation*.

Industry differences in government spending multipliers in New Keynesian small open economy models This essay is joint work with Sebastian Koch. The third essay studies government spending multipliers in an industry-level New Keynesian small open economy model calibrated with Austrian data. We show that the model predicts a very high heterogeneity across multipliers for government consumption in each of the 74 industries. Moreover, government investment multipliers vary substantially depending on the type of investment.

We show that the major sources of this heterogeneity are differences in import shares across industries, differences in production factor shares (especially labor share and intermediate input share) and asymmetry of the input-output network. The relative importance of these factors differs depending on the type of multiplier, considered time horizon, and persistence of the policy intervention. However, industry import shares are the most important determinant for all cases that we consider.

Our model questions the notion that governments should stimulate the economy by investing into infrastructure projects in bad times. In the model, temporary government investment shocks (with the exception of intangible investments, such as R&D) generate lower short run multipliers than government consumption in a number of service industries. Even though from a long-term perspective, investment is preferable due to its positive effects on the aggregate productivity, it takes time before these effects materialize. In the short run, government investment spending is more import-intensive, more likely to crowd out investment and intermediate inputs from the private sector and less likely to increase the income of credit-constrained households, which mitigates its expansionary effects.

A modified version of the model presented in the third essay has been used in the applied project of the Institute for Advanced Studies (IHS Vienna) *IHS model for impact-oriented evaluation of public policies*. Thus, parts of the model description closely resemble the (unpublished) technical documentation, see Koch et al. (2019).

Each of the three chapters is self-contained and can be read in isolation. However, the three models presented in this thesis share many commonalities, such as the disaggregated industry structure and similar household preferences. For the sake of better readability, I tried to keep the description of these features as close as possible across the three chapters, even though it means some repetitiveness. This also applies to data description and discussions. Since chapters 1 and 2 are based on the same data set, I omit the full data description in chapter 2 and refer to the appendix of chapter 1 instead.

1 Industry evidence and the vanishing cyclicality of labor productivity

1.1 Introduction

Business cycle fluctuations are often studied in terms of fixed relationships that generate stable co-movement patterns between economic variables. However, the nature of business cycle fluctuations in the U.S. have changed over the last 70 years. The procyclicality of aggregate labor productivity used to belong to the most strongly documented stylized facts in macroeconomics, but recent studies show it has largely disappeared.

In the 1980s, the robust empirical evidence on procyclical productivity actually led to the emergence of the real business cycle theory, in which the fluctuations of productivity are the driving force behind business cycles. The concept of productivity fluctuations as one of the driving forces behind macroeconomic fluctuations still continues to be influential in both academic and applied economics today.

However, more recent literature, including e.g. Stiroh (2009) and Galí and Gambetti (2009), pointed out that the procyclicality of measured aggregate productivity has largely disappeared since the mid-1980s. This observation challenges the validity of business cycle models based on the exogenous fluctuations of productivity, and more generally the validity of macroeconomic models which generate procyclical productivity exogenously or endogenously. Finding a sound explanation of the change in the co-movement patterns is important to reconcile the models to the data, with potentially big implications for economic theory. Numerous potential explanations of the vanishing procyclicality of productivity have been proposed in the macroeconomic literature, ranging from changes in cyclical measurement errors of production inputs and outputs (e.g. Galí and van Rens 2020, Berger 2018, Garin et al. 2018, Nucci and Riggi 2013, and McGrattan and Prescott 2010) to structural changes in composition of shocks and their effects on the economy (e.g. Galí and Gambetti 2009, Barnichon 2010, and Yépez 2017).

In this paper I contribute to the discussion by bringing in industry-level evidence, which I argue can help to discriminate between various explanations of the vanishing procyclicality of productivity. I first document the change in cyclical properties of productivity in the U.S. using industry-level data, which to my knowledge was only previously considered by Wang (2014). I use the dataset constructed by Dale Jorgenson and his co-authors (Jorgenson, 2008), which contains information about the U.S. economy between 1960 and 2005 disaggregated into 88 industries. My empirical observations are broadly in line with Wang (2014) but my focus is on documenting a particularly puzzling feature of the industry-level data: the correlations of industry productivity with industry output and labor input remained on average much more stable before and after the mid-1980s compared to the aggregate correlations. In other words, there is little evidence for vanishing pro-cyclicality of labor productivity at the industry level. At the same time, the change in composition of industries explains only a small part of the reduction of procyclicality of measured productivity. Instead, the majority of the decrease in correlations between aggregate productivity and output (resp. hours) can be attributed to the change in co-movement across industries.

After establishing these empirical observations I construct a simple industry-level RBC model that nests several explanations of the vanishing cyclicality of productivity proposed in the literature. I use the model to evaluate whether the proposed mechanisms are compatible with the industry-level evidence. Despite its simplicity, the model can qualitatively replicate the changes in the cyclical co-movement of measured aggregate productivity and other macroeconomic variables through two distinct mechanisms. The procyclicality of aggregate productivity in the model, measured in terms of correlations with labor input and output, decreases when the relative size of aggregate demand side shocks decreases compared to technology shocks, as suggested in, for example, Barnichon (2010). The procyclicality of aggregate productivity also decreases when the observed labor input (hours) becomes more flexible in comparison to the unobserved labor input margin (effort), as suggested in Galí and van Rens (2020).

Although both mechanisms are able to reduce the correlations of aggregate productivity with output and labor input, I show that they have qualitatively different predictions for the cyclical properties of industry-level variables. Within my model framework, the mechanism based on a structural change in the composition of aggregate shocks is able to replicate the stability of industry-level moments across time. In contrast, the mechanism based on a change in the flexibility of hours is less successful in matching the industry-level evidence.

It is important to mention that the change in the cyclical properties of labor productivity did not appear in isolation. Other potentially related changes appeared roughly at the same time, in the period referred to as the Great Moderation. The volatility of both aggregate output and labor input decreased in the mid-1980s (McConnell and Perez-Quiros, 2000), while the relative volatility of aggregate hours compared to output increased (Galí and Gambetti, 2009). The recoveries during the last three decades were untypically slow (Galí et al., 2012). In addition, there is some discussion on whether the lead-lag structure of employment and output has changed. After the three most recent recessions, some studies argued that in comparison to output, it took a relatively long time for employment to start recovering, an observation referred to as jobless recoveries; see e.g. Bernanke (2009), Jaimovich and Siu (2012), Berger (2018).

The rest of this paper is organized as follows: in the remainder of this section, I describe the relationship of the paper to the existing literature. I present the empirical findings in section 1.2. Section 1.3 describes the model. In section 1.4 I present the quantitative results and discuss the intuition behind these results in sections 1.5 and 1.6. Section 1.7 concludes.

1.1.1 Relationship to the existing literature

The analysis in this paper complements the extensive body of theoretical and empirical literature on change in cyclicality of productivity in the U.S. starting from Stiroh (2009) and Galí and

Gambetti (2009). The previous studies have documented a robust decline in correlations between measured aggregate productivity and aggregate output, resp. production inputs across the two time periods: first, the post-war period between 1950 and mid-1980s which I refer to as *pre-1984* period and second, the *post-1984* period from 1984 to up to 2015, where the end date depends on data availability.[1] Extensive empirical analyses have been conducted by Fernald and Wang (2016), Wang (2014), and Daly et al. (2017) among others.

Fernald and Wang (2016) provide an overview of the existing explanations of vanishing cyclicality of productivity and analyse the empirical evidence related to a wide range of these explanations. They make several important points based on the quarterly U.S. data series developed by Fernald (2014). Using the identification strategy based on Basu et al. (2006), Fernald decomposes the measured productivity series into *factor utilization* component and *utilization-adjusted TFP*, a purified measure of productivity which reflects the true technological progress more closely. Fernald and Wang (2016) find that (1) utilization-adjusted TFP was never really pro-cyclical before the mid-1980s, and it remained so,[2] (2) factor utilization was the procyclical component of measured productivity before the mid-1980s and it stayed procyclical,[3] and (3) the relative volatility of factor utilization compared to utilization-adjusted TFP substantially decreased in the period after 1984. The major part of the drop in cyclicality of measured productivity is explained by the decrease in volatility of the utilization component. Fernald and Wang stress that any theory aspiring to explain the vanishing procyclicality of aggregate productivity must necessarily be consistent with these three observations.

Wang (2014) is, to my knowledge, the only other paper analysing the industry-level evidence on vanishing cyclicality of productivity. Wang uses an alternative data set, 31 industry U.S. data published by World KLEMS (2010). The moment statistics reported by Wang are consistent with my own computations, however, the interpretation of the observed facts differs in some cases. Most noticeably, I stress that the correlations of industry-level productivity with industry-level output and labor input remained on average much more stable between the two periods compared to the aggregate correlations. Indeed, Wang (2014) also decomposes the aggregate correlations into the contribution of within-industry and cross-industry correlations and finds that the vast majority of actual change in the aggregate correlations comes from the cross-industry terms. She subsequently normalizes the contribution of the cross-industry terms by the disproportionally high number of cross-industry pairs and concludes that per industry pair, the contribution of within-industry changes is more important. I argue in this paper that there is no theoretical justification for such normalization and provide a model that formalizes the relationship between the industry-level and aggregate correlations.

In the succeeding extended literature discussion I loosely follow Fernald and Wang (2016) in classifying the explanations proposed in the literature into mechanisms based on (1) systematic measurement errors of inputs or outputs and (2) other structural explanations.

[1] I choose the breaking point between the two sub-periods in line with the rest of the literature to be the beginning of 1984.

[2] If anything, utilization-adjusted TFP became more correlated with inputs and outputs after the mid-1980s, not less correlated.

[3] The correlation of the utilization measure with labor input actually decreased for brief periods between 1990 and 2005, but the effect is less important than the drop in the volatility of factor utilization component.

The first group of explanations is based on some kind of cyclical measurement error of inputs or outputs. There would be no change in cyclicality of measured productivity if all the inputs and outputs were exactly accounted for. The mechanism that has attracted perhaps the most attention is based on the change in the efficiency of labor markets. Galí and van Rens (2020) argue that an improvement in the labor market matching technology effectively made adjusting the labor force less costly, which made firms rely less on adjusting unobservable intensive margins of production (such as labor utilization in form of unobserved labor effort, imperfectly measured overtime hours, or capital utilization) and more on adjusting the number of employees.[4] Galí and van Rens stress that this mechanism is simultaneously able to explain another change in the nature of macroeconomic fluctuations, namely the increase in relative volatility of aggregate hours compared to aggregate output. The basic idea behind the mechanism, which I also integrate into the model and explore in this paper, is described in Galí and van Rens (2020, pages 2-3) as follows:

Suppose that firms have two margins for adjusting their effective labor input: (observed) employment and (unobserved) effort, which are denoted (in logs) by n and e, respectively.[5] Both margins of labor input are transformed into output according to a standard production function,

$$y = (1-\alpha)(n+e) + a, \tag{1.1}$$

where a is log total factor productivity and α is a parameter measuring diminishing returns to labor. Measured labor productivity, or output per worker, is given by

$$y - n = -\alpha n + (1-\alpha)e + a. \tag{1.2}$$

Labor market frictions make it costly to adjust employment n. Since these adjustment costs are convex, frictions are higher when the average level of hiring is higher. Effort provides an alternative margin of adjustment of labor input and is not subject to those frictions (or to a lesser degree). Thus, the larger the frictions, the less employment fluctuates and the more volatile are fluctuations in effort. Reduced hiring frictions decrease the volatility of effort and therefore increase the relative volatility of employment with respect to output. The increased volatility of n also makes labor productivity less procyclical, and, in the presence of shocks other than shifts in technology, may even make productivity countercyclical.

Other papers featuring similar mechanisms include Barnichon (2010), Lewis et al. (2019), Evans (2019) and Nucci and Riggi (2013). An alternative channel through which higher flexibility in the labor markets may have played a role is that firms might be able to better identify less productive workers and lay them off more selectively during bad times. Berger (2018) suggests that this can explain both the good performance of labor productivity in recessions and the slow recovery of employment afterwards. Although there is no unmeasured labor input margin present in this mechanism, the heterogeneous workers' quality creates a wedge between observed and

[4] The idea goes back to a literature, starting with Oi (1962) and Solow (1964), which attributes the procyclicality of productivity to variations in effort, resulting in seemingly increasing returns to labor.

[5] To simplify the argument, we assume hours per worker are constant, consistent with the observation that in the US data most adjustments in total hours worked take place along the extensive margin.

effective labor input. The implications from my model can not directly speak to the mechanism proposed by Berger, but it is likely that increased selective hiring, similar to other explanations based on the labor market flexibility, would also generate substantial changes at the industry level. Riggi (2019) proposes another alternative mechanism based on efficiency wages that is able to generate countercyclical work effort if firms imperfectly detect shirking workers. An improvement in monitoring possibilities of firms in her model can generate a decrease in the correlation between measured productivity and labor input. However, the volatility of labor utilization in this case increases, which is not in line with the observations made by Fernald and Wang (2016).

Another idea connected to the systematic measurement errors that my model does not directly address is that the growing importance of intangible investment might have led to systematic errors in measurement of output; see McGrattan and Prescott (2010), McGrattan (2017). To the extent that intangible investment activity is procyclical, measured productivity may have become less correlated with measured output if intangible output became more important.

However, the higher share of unmeasured intangible investment in output also does not explain why the volatility of the factor utilization component constructed by Fernald (2014) became less volatile compared to the utility-adjusted TFP. The factor utilization component is identified based on the fluctuations of observed hours per worker, a margin that is not directly affected by the share of intangible investment. Thus, the mechanism is not in line with the empirical observations made by Fernald and Wang (2016). Moreover, Wang (2014) uses the observed intensity of ICT-investment at industry level as a proxy for the intangible investment, assuming complementarity between the two margins. Wang finds little evidence that intangible investment explains the decline in cyclicality of measured productivity. Nevertheless, one must stress that assessing the role of intangible investment inherently suffers from data limitations, as intangible investment activities are hard to measure. McGrattan (2017) makes a considerable contribution in this respect by improving the existing industry-level datasets to better reflect the increasing importance of intangible investment.

A further mechanism that gives rise to a wedge between measured and actual productivity at aggregate and industry level is reallocation. Garin et al. (2018) suggest that procyclical reallocation became much more prominent since the mid-1980s due to the increased importance of industry-specific shocks documented, for example, by Foerster et al. (2011). Although I also analyse the role of changing importance of aggregate shocks, my model does not feature any reallocation friction. Fernald and Wang (2016) argue that the reallocation component also does not enter the factor utilisation term, making it an unlikely main driver of vanishing cyclicality of aggregate labor productivity. However, this mechanism could have contributed to the observed changes.

Lastly, it is clear that the U.S. economy has undergone substantial changes in composition over the last 70 years. Carvalho and Gabaix (2013) have argued that a substantial part of the decrease in variance of macroeconomic variables in the Great Moderation can be explained by the changes in composition of industries. However, in line with Wang (2014) I show in section 1.2 that the changes in composition only explain a minor part of the observed change in cyclicality of measured productivity.

The second broad group of explanations has related the observed changes in the cyclical behaviour of macroeconomic variables more directly to changes in relative importance of various types of shocks, or the way in which the shocks affect the economy. Numerous studies have identified a change in the size and composition of different types of shocks after the mid-1980s. Some authors argued that the Great Moderation can be accounted to good luck (Justiniano and Primiceri 2008, Arias et al. 2007). Others have attributed the changes to a different policy conduct or changing structure of the economy in general; see e.g. Clarida et al. (2000), Kahn et al. (2002), Galí and Gambetti (2009), Dynan et al. (2006), Yépez (2017).

Barnichon (2010) and Galí and Gambetti (2009) connect the vanishing cyclicality of productivity to the observation that aggregate demand shocks have become less volatile relative to aggregate technology shocks after the mid-1980s. Different types of shocks, for example technology or monetary policy shocks, naturally affect the measured productivity differently. Because the responses of macroeconomic variables to various shocks depend on the model framework, the effect of changes in shock composition on the cyclicality of productivity can only be studied within a given model. Both empirically and within a typical New-Keynesian model framework, technology improvements raise the measured productivity but cause hours to contract in the short run; see e.g. Galí (1999). Therefore, greater importance of technology shocks implies that the share of utilization-adjusted TFP in the measured productivity grows and, simultaneously, that the correlation of measured productivity with inputs decreases. This is also the case in my model, which features both demand side and technology aggregate shocks.

In the remainder of this paper, I concentrate on the two most prominent mechanisms from both strands of the literature, the labor market flexibility explanation and the shock composition explanation. I build an industry-level model that, in a simple form, nests the mechanisms from Galí and van Rens (2020) and Barnichon (2010). I replicate the aggregate implications of these papers and compare their industry-level predictions with the evidence.

In order to keep the main insights of my paper intuitive and tractable, I keep the industry structure of the economy as simple as possible. I abstract from using the realistic industry composition and the input-output linkages between industries. Nevertheless, it is important to mention that this simplification is not innocuous. A rich literature documents the important role of industry structure and the input-output linkages for generating realistic co-movement patterns between the industry-level economic variables; see e.g. Horvath (2000), Dupor (1999), Acemoglu et al. (2012), Holly and Petrella (2012), Atalay (2017). The industry structure also influences the extent to which industry-specific shocks propagate across industries, and therefore determines the relative importance of aggregate and industry-specific shocks necessary to generate the realistic economic fluctuations at both the industry and aggregate level. For this reason, my model is not able to generate the realistic co-movement patterns observed across industries in the U.S. economy.

1.2 Empirical evidence: Changes in cyclicality of productivity at the aggregate and industry level

In this section I present the empirical evidence on the change in cyclicality of measured productivity and other macroeconomic variables in the U.S. in the periods before and after 1984. I first introduce the data source and show that the aggregate moments constructed using the data are consistent with the findings in the existing literature. I then continue by analysing the industry-level evidence. I find that the industry-level correlations remained on average much more stable across the two time periods compared to the aggregate correlations. I analyse the effect of industry composition and find that it only contributed a minor part of the observed changes of aggregate correlations. In order to shed more light on these seemingly inconsistent industry-level observations I decompose the aggregate correlations into the contribution of within-industry and cross-industry correlations and find that the vast majority of the actual change in aggregate correlations comes from decreased co-movement across industries.

1.2.1 Data

The primary data source that I use is the KLEMS growth accounting data set developed by Dale Jorgenson and his co-authors (Jorgenson 2008). The data set provides annual information on capital, labor and intermediate inputs and outputs of the U.S. economy between 1960 and 2005 disaggregated into 88 industries. Most of the literature so far has focused on analysing aggregate-level data, such as from the BLS Labor Productivity and Cost (LPC) program, which are available at higher frequency, but do not contain industry-level information. In line with the literature I focus on the private business sector which consists of 77 industries.

I use the standard bottom-up KLEMS methodology in order to construct the aggregate series from the industry-level data; see e.g. Timmer et al. (2007a). I also rely on the KLEMS methodology for computing the two standard measures of productivity: labor productivity and total factor productivity (TFP). I thus define the measured labor productivity as value added per effective hour and measured TFP as the usual Solow residual.[6] While most of the existing literature reports results for both measured labor productivity and TFP, Wang (2014) argues for focusing on TFP as a cleaner measure of productivity.

The measure of labor input reported in Jorgenson's dataset is effective hours. Effective hours are defined as total hours adjusted for the composition of the workforce, taking into account some observable characteristics (education, age and gender). The details describing the construction of data series and the moments are provided in appendix 1.A.

1.2.2 Change in cyclicality of aggregate productivity

Previous literature has documented significant differences in cyclicality of productivity in the U.S. between periods pre- and post-1984. The correlation of measured aggregate labor productivity with output went from strongly procyclical to acyclical, while correlation of measured aggregate labor

[6] My measure of TFP at both aggregate and industry level is value added-based, not gross output-based Solow residual. The difference between the two measures only affects the scaling of the productivity series.

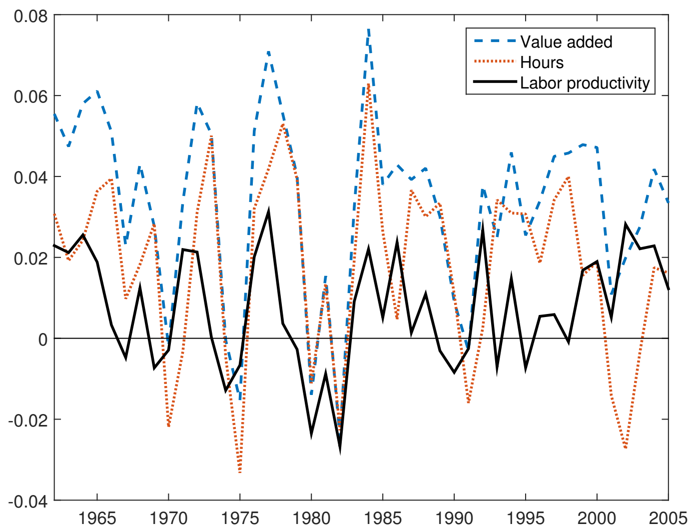

Figure 1.1: Aggregate variables constructed from industry-level Jorgenson (2008) data set: annual growth rates of value added, hours, and labor productivity.

productivity with labor input went from weakly procyclical to countercyclical. The aggregate stylized facts computed from the industry-level Jorgenson data set are consistent with these observations: various measures of cyclicality of aggregate productivity have substantially decreased since the mid-1980s. Figure 1.1 plots the annual growth rates of aggregate value added, hours, and labor productivity constructed from the Jorgenson data.

To document the aggregate changes, I compute four correlations: between measured aggregate labor productivity (LP) resp. total factor productivity (TFP) and aggregate value added (VA) resp. hours (H). I compute each of the correlations using four different detrending methods. I use growth rates (first differences), Christiano-Fitzgerald band-pass filter that isolates the frequencies between 2 and 8 years, and Hodrick-Prescott filter with smoothing parameters $\lambda = 100$, resp. $\lambda = 6.25$.[7]

Table 1.1 reports the cyclical correlations for the two time periods of interest. The correlation of measured aggregate labor productivity with hours decreased sharply from weakly procyclical to strongly countercyclical, with the difference between the two sub-periods ranging from -0.58 to -0.85 depending on the detrending method. The correlation of labor productivity with output decreased from procyclical to basically acyclical, with the difference ranging between -0.29 and -0.58. The table also shows that measured TFP is consistently more procyclical than labor productivity. This is not surprising, as capital is relatively rigid compared to labor input and capital intensity is thus countercyclical. The important observation is that even though measured TFP is in general more procyclical than labor productivity, its cyclicality also decreased substantially between the two sub-periods, and the magnitude of the change is comparable with the cyclicality of labor productivity.

The correlations are qualitatively in line with the previous literature. Correlations of productivity measures with output are directly comparable to Wang (2014), who also uses annual industry-level data set to construct the moments. Correlations are quantitatively in line with Wang for

[7] Both values of the smoothing parameter have been used in the literature to which I relate.

	1960-2005	1960-1983	1984-2005	Difference
corr(TFP, VA)				
First Diff.	0.72	0.85	0.46	-0.39
CF	0.82	0.85	0.70	-0.14
HP par=100	0.68	0.86	0.15	-0.71
HP par=6.25	0.76	0.85	0.40	-0.45
corr(TFP, H)				
First Diff.	0.22	0.52	-0.27	-0.79
CF	0.45	0.56	0.08	-0.48
HP par=100	0.23	0.61	-0.46	-1.06
HP par=6.25	0.37	0.60	-0.26	-0.86
corr(LP, VA)				
First Diff.	0.32	0.49	0.11	-0.37
CF	0.40	0.49	0.20	-0.29
HP par=100	0.31	0.57	-0.01	-0.58
HP par=6.25	0.29	0.47	-0.03	-0.50
corr(LP, H)				
First Diff.	-0.29	0.04	-0.63	-0.66
CF	-0.10	0.10	-0.49	-0.58
HP par=100	-0.23	0.20	-0.64	-0.85
HP par=6.25	-0.21	0.11	-0.67	-0.78

Table 1.1: Cyclical correlations between selected productivity measures and output, resp. hours. Comparison pre- and post-1984. Each correlation is computed using four different detrending methods.

Standard deviation	1960-2005	1960-1983	1984-2005	Difference
Value added (VA)	2.25	2.73	1.62	-1.12
Hours (H)	2.23	2.39	2.06	-0.33
$\mathrm{std}(H)/\mathrm{std}(VA)$	0.99	0.87	1.27	0.40
$\mathrm{std}(TFP)/\mathrm{std}(VA)$	0.63	0.58	0.71	0.13

Table 1.2: Volatility (in percent) and relative volatility of selected aggregate variables. Comparison pre- and post-1984. Moments computed for growth rates of the variables.

most of the filtering methods, with minor differences attributable to the differences between data sets. The comparison of my results with the correlations reported in Wang (2014) and the correlations based on quarterly aggregate data reported by Galí and van Rens (2020) is provided in appendix 1.B.

I omit the computation of standard errors for the aggregate second moments. The statistical significance of the observed changes has been tested multiple times by the previous studies using the quarterly data. The annual data set I work with contains fewer observations, hence the statistical significance at the aggregate level is weaker. However, the purpose of this exercise is to confirm the consistency with the existing empirical observations, not to provide new evidence on changing aggregate correlations.

Table 1.2 reports another important set of moments, standard deviations and relative standard deviations of selected aggregate variables, reported for the growth rates. In line with the existing literature I find that while both volatility of output and hours has decreased, the relative volatility of aggregate hours compared to output has increased between the two sub-periods. The comparison with the moments reported in Galí and van Rens (2020), as well as results for other detrending methods, are provided in appendix 1.B.

	1960-2005	1960-1983	1984-2005	Difference
corr(TFP, VA)				
First Diff.	0.80	0.81	0.79	-0.02
CF	0.82	0.81	0.84	0.03
HP par=100	0.78	0.79	0.76	-0.04
HP par=6.25	0.81	0.81	0.81	0.01
corr(TFP, H)				
First Diff.	-0.10	0.00	-0.21	-0.21
CF	-0.02	0.08	-0.11	-0.19
HP par=100	-0.14	-0.03	-0.27	-0.24
HP par=6.25	-0.06	0.05	-0.17	-0.22
corr(LP, VA)				
First Diff.	0.73	0.73	0.71	-0.02
CF	0.72	0.71	0.74	0.02
HP par=100	0.72	0.71	0.70	-0.01
HP par=6.25	0.72	0.71	0.71	0.00
corr(LP, H)				
First Diff.	-0.30	-0.22	-0.40	-0.18
CF	-0.23	-0.13	-0.32	-0.19
HP par=100	-0.32	-0.22	-0.42	-0.21
HP par=6.25	-0.27	-0.16	-0.38	-0.21

Table 1.3: Average industry-level cyclical correlations between selected productivity measures and output, resp. hours. Weighted averages using constant industry weights over time: average nominal output share between 1960 and 1983. Comparison pre- and post-1984. Each correlation is computed using four different detrending methods.

Standard deviation	1960-2005	1960-1983	1984-2005	Difference
Value added (VA)	7.82	8.02	7.62	-0.40
Hours (H)	4.79	5.04	4.33	-0.71
$\mathrm{std}(H)/\mathrm{std}(VA)$	0.61	0.63	0.57	-0.06
$\mathrm{std}(TFP)/\mathrm{std}(VA)$	0.92	0.92	0.93	0.01

Table 1.4: Average volatility (in percent) and average relative volatility of selected industry-level variables, growth rates. Weighted averages using constant industry weights over time: average nominal output share between 1960 and 1983. Comparison pre- and post-1984.

1.2.3 Industry evidence

This section reports the moments at the industry level. Table 1.3 displays the correlations analogous to table 1.1, but instead of aggregate correlations it displays weighted averages across the 77 industry-level correlations. The correlations are weighted by industry nominal output shares in the pre-1984 period. However, the results reported in table 1.3 are robust with respect to alternative choices of weights.

The industry-level results in table 1.3 differ qualitatively from the patterns observed for the aggregate correlations. On average, the correlation of measured industry productivity with industry output stayed virtually unchanged for both measures of productivity. Although there is on average a decrease in the correlations between industry productivity and industry hours, the difference between the two sub-periods is much smaller compared to the aggregate correlations. Moreover, table 1.4 shows that the average relative volatility of industry hours in comparison to industry output stayed virtually unchanged. This striking difference between the industry-level

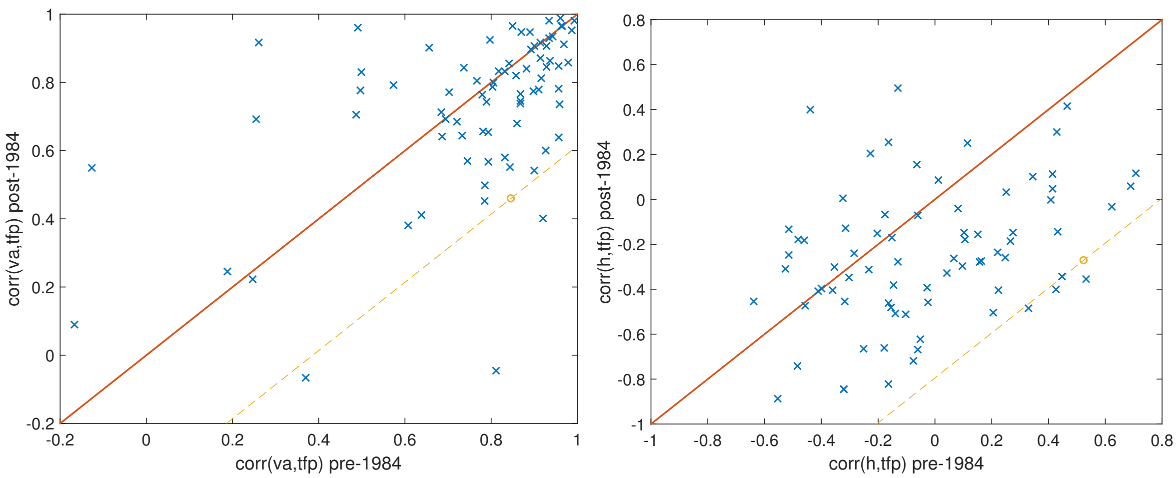

Figure 1.2: Correlations between measured industry TFP and value added (left) resp. hours (right). Comparison pre-1984 (x-axis) and post-1984 (y-axis). The red 45° line illustrates no change in correlations between the two sub-periods. The yellow dashed line illustrates the change in corresponding aggregate correlation.

and aggregate correlations is the main motivation for conducting an analysis of the changes in cyclicality of productivity using the industry-level evidence.

Because the moments reported in tables 1.3 and 1.4 are crucial for the remainder of this paper, I briefly discuss their robustness. Complementary evidence is reported in appendix 1.B. Firstly, the stable industry-level correlations are not an artefact of the particular choice of weighting. The results are robust with respect to weighting by the nominal output shares in the second sub-period, or computing simple averages. Figure 1.2 depicts the individual industry-level correlations for periods pre- and post-1984 for the 77 industries. For many industries the correlations in the first and second sub-period differ substantially. However, there is no clear pattern showing a consistent decrease in correlations between output and measured productivity (left panel). The correlations between hours and productivity depicted in the right panel decreased for the majority of industries, however, the changes for most of the industries are relatively small. Only in four cases has the correlation between industry hours and productivity decreased in absolute value as much as the aggregate correlation, illustrated by the yellow dashed line. It is worth noting that the puzzling evidence in table 1.3 cannot be explained by the possibility that a small number of very big industries became more countercyclical in the second sub-period and in turn, affected the aggregate correlations. The industry averages reported in the table are already weighted by the industry size, thus taking this effect into account.

I use bootstrapping in order to compute the standard errors of the average correlations reported in table 1.3. The bootstrapped standard errors are small, see appendix 1.B for details.

Industry composition

Figure 1.2 reveals a substantial heterogeneity of correlations at the industry level. A possible explanation of how the aggregate correlations could have changed, even though the industry-level correlations on average stayed the same, is that the composition of industries might have changed. The procyclicality of aggregate productivity could decrease as a consequence of industries with

	1960-2005	1960-1983	1984-2005	Difference
corr(TFP, VA)				
Aggregate series	0.72	0.85	0.46	-0.39
Fixed composition	0.70	0.83	0.51	-0.32
corr(TFP, H)				
Aggregate series	0.22	0.52	-0.27	-0.79
Fixed composition	0.22	0.53	-0.19	-0.72
corr(LP, VA)				
Aggregate series	0.32	0.49	0.11	-0.37
Fixed composition	0.43	0.60	0.27	-0.33
corr(LP, H)				
Aggregate series	-0.29	0.04	-0.63	-0.66
Fixed composition	-0.13	0.22	-0.46	-0.67

Table 1.5: Cyclical correlations between selected productivity measures and output, resp. hours. Comparison of aggregate series and counterfactual fixed-composition aggregate series, pre- and post-1984. Detrending method: growth rates.

countercyclical productivity growing bigger. I isolate the effect of composition by constructing counterfactual aggregate series in which I keep the industry composition constant over time. A comparison of the moments computed using the actual aggregate data versus the *fixed-composition* aggregate series shows that composition only played a minor role in decreasing the cyclicality of productivity.

According to the standard growth accounting, growth rate of any aggregate variable X_t can be approximately expressed as

$$\tilde{X}_t \approx \sum_{i=1}^{N} w_{i,t}\tilde{x}_{i,t}, \tag{1.3}$$

where $\tilde{x}_{i,t}$ is the growth rate between periods t and $t-1$ of industry-level variable x_i, and $w_{i,t}$ is an appropriately chosen time varying weight of industry i. The derivation of the approximation, weights, and a discussion on the quality of this approximation in the data set is provided in appendix 1.C.

I examine the counterfactual scenario in which the composition of the U.S. economy stays constant over time. I aggregate the industry level series using weights $\bar{w}_i$ that are fixed over time. I choose the weights to be the average shares of appropriately chosen nominal variables over the pre-1984 period, although the results are robust with respect to alternative choices of weighting. I plot the fixed-composition aggregate series and provide comparisons with the original aggregate series in appendix 1.C. If the composition effect is big, fixing the aggregation weights should substantially change the aggregate series, and consequently their second moments.

However, industry composition seems to have a small effect on the change in cyclicality of aggregate productivity. Table 1.5 compares the correlations for aggregate growth rates from table 1.1 with the analogous correlations computed using fixed-composition aggregate series. Composition has somewhat countercyclical effect in case of measured labor productivity, but this effect is present in both sub-periods. Importantly, as the last column of table 1.5 shows, the correlations between measured productivity and output resp. hours computed using the fixed-composition series decrease between the two sub-periods. The decrease is comparable with the actual aggregate series, reaching between 80% and 100% of the latter. The decrease in cyclicality of measured TFP for fixed composition series is quantitatively very similar to the results in table 1.1 in the case of growth rates and the Christiano-Fitzgerald band-pass filter, and somewhat smaller for the Hodrick-Prescott filtered series. The results for other detrending methods are reported in table 1.16 of appendix 1.C. I omit the calculation of standard errors as the point of the exercise is to isolate a component of observed changes in the actual observations.

I conclude that a substantial part of the decrease in cyclicality of productivity is not explained by changes in composition of industries, although I can not rule out that the composition of industries had some effect on the observed changes. As I have already shown above that the industry-level correlations also did not change between the two periods, the limited effect of composition might occur puzzling. In the next section, I shed more light on this issue by formally decomposing the change in cyclicality of aggregate productivity into the contribution of within-industry and cross-industry components.

Changing co-movement within industries and across industries

In what follows, I focus on the fixed-composition aggregate series described in the previous section. I work with the growth rates series, which are straightforward to decompose into a weighted sum of industry-level series. I defined the (growth rate of) fixed-composition aggregate variable $\bar{X}_t$ as

$$\bar{X}_t := \sum_{i=1}^{N} \bar{w}_i^X \tilde{x}_{i,t} \approx \tilde{X}_t, \tag{1.4}$$

where tilde denotes growth rates of variables and $\bar{w}_i^X$ are constant industry weights. For any pair of aggregate series $\bar{X}$, $\bar{Y}$ defined as in equation 1.4, the correlation coefficient can be decomposed into a within-industry and a cross-industry component as follows:

$$\begin{aligned}
\text{Corr}\left(\bar{X}, \bar{Y}\right) &= \frac{\text{Cov}(\sum_{i=1}^N \bar{w}_i^X \tilde{x}_i, \sum_{i=1}^N \bar{w}_i^Y \tilde{y}_i)}{\text{std}\left(\bar{X}\right)\text{std}\left(\bar{Y}\right)} && (1.5)\\
&= \frac{\sum_{i=1}^N \bar{w}_i^X \bar{w}_i^Y \,\text{Cov}(\tilde{x}_i, \tilde{y}_i)}{\text{std}\left(\bar{X}\right)\text{std}\left(\bar{Y}\right)} + \frac{\sum_{i=1}^N \sum_{j\neq i}^N \bar{w}_i^X \bar{w}_j^Y \,\text{Cov}(\tilde{x}_i, \tilde{y}_j)}{\text{std}\left(\bar{X}\right)\text{std}\left(\bar{Y}\right)}. && (1.6)
\end{aligned}$$

The first term of equation 1.6 collects the diagonal elements and reflects the co-movement between variables within individual industries. The second term collects all the off-diagonal elements and reflects the co-movement pattern across industries. The decomposition makes it clear that the aggregate correlation between variables might change as a consequence of changing co-movement patterns between industries, even when the within-industry co-movement stays the same.

Table 1.6 shows the result of the decomposition for the four aggregate correlations reported in table 1.5 for periods pre- and post-1984. The decomposition shows that the bulk of the decrease in cyclicality of productivity comes from the cross-industry component, reflecting the lower co-movement between industries. The within-industry component is in fact again an alternatively weighted average of the industry-level correlations. Its contribution to the change between the sub-periods is small, in line with the evidence in table 1.3. The change of the contribution of

	1960-2005	1960-1983	1984-2005	Difference
corr(TFP, VA)				
Total correlation	0.70	0.83	0.51	-0.32
Within-industry comp.	0.22	0.19	0.29	0.10
Cross-industry comp.	0.48	0.64	0.21	-0.43
corr(TFP, H)				
Total correlation	0.22	0.53	-0.19	-0.72
Within-industry comp.	-0.01	-0.00	-0.02	-0.02
Cross-industry comp.	0.23	0.53	-0.17	-0.70
corr(LP, VA)				
Total correlation	0.43	0.60	0.27	-0.33
Within-industry comp.	0.22	0.22	0.24	0.02
Cross-industry comp.	0.21	0.38	0.03	-0.35
corr(LP, H)				
Total correlation	-0.13	0.22	-0.46	-0.67
Within-industry comp.	-0.05	-0.05	-0.05	-0.00
Cross-industry comp.	-0.09	0.26	-0.41	-0.67

Table 1.6: Decomposition of cyclical correlations between selected productivity measures and output, resp. hours into within-industry and cross-industry component. Comparison pre- and post-1984. Fixed-composition aggregate series constructed using average pre-1984 industry weights.

diagonal elements is very small for all four correlations, in two cases it is even positive. The cross-industry component, on the other hand, constitutes the vast majority of the change in aggregate correlations. The difference between the two components appears striking, but it requires a careful interpretation.

While the decompositions are in terms of numbers in line with Wang (2014), we differ in terms of interpretation of the numbers. Wang computes the contribution of within- and cross-industry term to the correlation between measured TFP and input aggregate (consisting of appropriately weighted hours, capital, and intermediate inputs). She finds that the contribution of the within-industry component is 0.016 before 1984 and -0.078 after 1984. The change in the contribution of within-industry component is therefore -0.094, higher than in my decomposition. Nevertheless, it is smaller than -0.52, the contribution of the cross-industry component. The somewhat bigger (in absolute value) contribution of diagonal elements is partly attributable to a smaller number of industries used by Wang (2014).

Wang divides the contributions of diagonal and off-diagonal terms by the number of elements in each of the sums in equation 1.6, effectively scaling down the contribution of the off-diagonal component by the number of industries. She then interprets the result as within-industry changes being much more (five times more) important for the change of cyclicality of productivity than the cross-industry changes. However, I argue that this interpretation has several shortcomings:

- Normalizing the contribution of within- and cross-industry terms by the number of elements has no theoretical justification. In general, any change in co-movement of a single industry variable affects both the within-industry and cross-industry term. However, relative importance of these effects depends on the properties of data generating process, which are ex ante unknown. In my view, the best way to interpret the empirical results is to build an industry-level model and analyse its predictions for within-industry and cross-industry second moments.

- The conclusion provided in Wang (2014) is not robust. The result is very sensitive with respect to small changes in the contribution of the diagonal elements. My decomposition results show that the contribution of within-industry elements is positive, not negative, for two out of four correlations. This would completely reverse the conclusions of Wang (2014), even though the differences are small in absolute terms.

In the next section, I build a simple industry-level model which nests different mechanisms that are able to generate changes in the aggregate correlations. I compare the predictions of the model for aggregate and industry-level moments with the evidence summarized in this section. Most importantly, I assess the ability of the proposed mechanisms to generate the changes in aggregate correlations, while keeping the industry-level moments stable in line with tables 1.3 and 1.4.

1.3 Model

This section presents a simple multi-industry general equilibrium model that nests several explanations of the vanishing procyclicality of productivity that have been proposed in the literature. The procyclicality of measured productivity in the model decreases when the relative size of aggregate demand shocks decreases compared to the shocks to productivity (as in Barnichon 2010), or when the observed labor input (hours) becomes more flexible (as in Galí and van Rens 2020). The model is relatively close to Galí and van Rens (2020), the main innovation being that I model the economy at the level of industries. On the other hand, I keep the labor market simpler, in that I abstract from the explicit labor market friction.

The most essential features of the model are:

- production sector consisting of industries, products of which are imperfectly substitutable
- observable and unobservable labor supply margins, which create a wedge between measured and actual productivity
- demand- and supply-side shocks which affect either the aggregate economy as a whole, or have industry-specific effects

The economy is populated by a continuum of representative households and a continuum of firms belonging to one of N symmetric industries. As there is no saving technology for the households and no capital, both the households and the firms solve a static problem in each period.

1.3.1 Firms

Each industry consists of a continuum of identical perfectly competitive firms represented by the unit interval. A firm belonging to industry i produces output according to the production function

$$y_i = z_i l_i^{1-\alpha}, \tag{1.7}$$

where z_i is industry-specific technology, l_i is effective labor input of a firm in industry i, and $\alpha \in (0,1)$ is a parameter that measures diminishing returns to labor. The effective labor input l_i depends on hours worked h_i and effort per hour e_i,

$$l_i = e_i h_i. \tag{1.8}$$

Effort in the model is the measure of workers' performance that can include any unobserved margins typically considered to be a part of labor utilization, e.g. unreported overtime hours or idle workers' time. Both hours and effort are provided by the households and are observable by the firm. The key difference between the two margins is that effort is typically not observable by the econometricians – standard measures of productivity therefore rely on the observable hours.

Industry specific technology z_i consists of two exogenous stochastic components, the idiosyncratic industry technology $\bar{z}_i$ and aggregate technology A

$$z_i = A\bar{z}_i, \tag{1.9}$$

where both components are random variables following $\ln(\bar{z}_i) \sim \mathcal{N}(0, {\sigma^z}^2)$ and $\ln(A) \sim \mathcal{N}(0, {\sigma^A}^2)$.

The problem of a representative firm in industry i is therefore to maximize profit

$$p_i z_i {l_i}^{1-\alpha} - w_i l_i, \tag{1.10}$$

taking as given the wage per unit of efficient labor input w_i and the industry good price p_i. An optimizing firm chooses l_i such that the marginal profit of increasing the effective labor input equals the marginal costs

$$(1-\alpha) p_i z_i {l_i}^{-\alpha} = w_i. \tag{1.11}$$

Firm profits d_i are distributed to households as lump sum payments

$$d_i = \alpha p_i z_i {l_i}^{1-\alpha}. \tag{1.12}$$

1.3.2 Households

There is a continuum of identical households represented by the unit interval. Households provide labor input and consume goods. The objective of the representative household is to maximize its period utility

$$D \cdot u(C) - \sum_{i=1}^{N} g(e_i, h_i). \tag{1.13}$$

The consumption bundle C is defined as

$$C = \left(\sum_{i=1}^{N} {v_i}^{\frac{1}{\sigma}} {c_i}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{1.14}$$

where c_i is the consumption of industry i good and v_i is exogenous stochastic weight of industry i in the consumption bundle. I interpret the weight v_i as industry-specific demand shock.[8] Parameter $\sigma > 0$ is the elasticity of substitution between goods produced in various industries. The consumption bundle serves as the numeraire and all prices are expressed relative to its price.

Function $u(\cdot)$ measures the utility derived from consumption. It is continuous, concave and increasing in C. In all numerical exercises I assume CRRA preferences $u(C) = \frac{C^{1-\rho}}{1-\rho}$, where $\rho > 0$. Preference shock D is an exogenous stochastic variable that is again drawn from a log-normal distribution. In line with Galí and van Rens (2020) I interpret it as a stand in for any non-technology aggregate disturbances.

Function $g(\cdot)$ measures the disutility of working. It is continuous, convex and increasing in both hours h_i and effort e_i. The functional form used in this paper follows Barnichon (2010) and Bils and Cho (1994), and nests the special case in Galí and van Rens (2020):

$$g(e,h) = \lambda_h h^{1+\eta} + \lambda_e h e^{1+\epsilon}, \tag{1.15}$$

where $\lambda_h, \lambda_e, \eta, \epsilon > 0$. This form of $g(\cdot)$ implies that the disutility of effort per hour increases with hours worked. Parameters η and ϵ determine the elasticity of hours and effort.

The household utility function 1.13 is separable in labor supply across industries and includes the special case in which the utility of consumption is also separable, $\sigma = 1/\rho$. The separability assumption is not innocuous, but it allows me to keep the formulas simple and derive some intuitive insights analytically.

The representative household faces a budget constraint,

$$\sum_{i=1}^{N} w_i l_i + \sum_{i=1}^{N} d_i = \sum_{i=1}^{N} p_i c_i. \tag{1.16}$$

In equilibrium, both labor and goods market must clear in each industry, thus

$$c_i = y_i. \tag{1.17}$$

In the following sections I discuss three dimensions of optimal household behaviour: the optimal composition of consumption bundle, composition of labor input and total labor supply decision.

Optimal composition of consumption bundle

Recall that all prices are expressed relative to the price of consumption bundle. Given the price of industry i good, the optimal demand for the industry i good is iso-elastic given by

$$c_i = v_i {p_i}^{-\sigma} C, \tag{1.18}$$

[8] I normalize the industry-level demand shock such that its aggregate effect is neutralised, $v_i = \bar{v}_i / \sum_{i=1}^{N} \bar{v}_i$, where $\ln(\bar{v}_i) \sim \mathcal{N}(0, {\sigma^v}^2)$.

and the definition of price index ensures that

$$C = \sum_{i=1}^{N} p_i c_i. \tag{1.19}$$

The elasticity of substitution σ determines the reaction of the nominal output share of good i to the change in its price. In the case of σ equal to one, the output share of each good is independent of its relative price. A positive shock to technology z_i reduces the optimal price set by the competitive firms exactly by the size of the shock. Thus, the increase in the real demand of good i caused by the reduced price is exactly satisfied by the improvement in technology. For σ equal to one, industry labor input does not respond to changes in industry technology.

Optimal composition of labor input

Given the firm demand for labor in each industry $\bar{l}_i$, household may provide any combination of hours and effort that satisfies $\bar{l}_i = e_i h_i$. Therefore, the representative household solves N independent industry problems,

$$\min_{e_i, h_i} g(e_i, h_i) \tag{1.20}$$

$$\text{s.t.} \qquad \bar{l}_i = e_i h_i. \tag{1.21}$$

The first order conditions of the problem give

$$\frac{\partial g(e_i, h_i)/\partial e_i}{\partial g(e_i, h_i)/\partial h_i} = \frac{h_i}{e_i}. \tag{1.22}$$

As function g is increasing in both e_i and h_i, the term on the left hand side is positive and the households will always adjust both margins simultaneously in the same direction. Given the functional form 1.15, equation 1.22 implies

$$e_i = \left(\frac{\lambda_h}{\lambda_e} \frac{(1+\eta)}{\epsilon} \right)^{\frac{1}{1+\epsilon}} h_i^{\frac{\eta}{1+\epsilon}}. \tag{1.23}$$

The elasticity of effort with respect to hours thus depends on the term $\frac{\eta}{1+\epsilon}$, which I somewhat loosely refer to as the *elasticity ratio.*

Labor supply decision

Finally, the optimizing representative household chooses non-negative values for consumption c_i, effort e_i, and hours h_i that maximize the utility function 1.13 given the budget constraint 1.16. Using the optimal firm behaviour condition 1.11, the budget constraint can be expressed as

$$\sum_{i=1}^{N} p_i z_i (e_i h_i)^{1-\alpha} = C. \tag{1.24}$$

Differentiating the Lagrangian associated with the household problem with respect to c_i and h_i and combining the associated first order conditions leads to the equation which determines the labor supply in the economy,

$$w_i e_i D C^{-\rho} = \frac{\partial g(e_i, h_i)}{\partial h_i} = \frac{\partial g(e_i, h_i)}{\partial e_i} \frac{e_i}{h_i}, \tag{1.25}$$

where the latter equation follows from 1.22. Similarly to many other RBC models, the response of hours to a technology shock can be both positive or negative and depends on the value of elasticity parameter ρ. In the case of log-utility ($\rho = 1$), an increase in real wages following a technology shock is exactly offset by a decrease in marginal utility of consumption, thus the labor supply stays constant.

1.3.3 Equilibrium and model solution

The equilibrium in variables C, h_i, e_i, w_i, p_i, y_i and c_i is defined by the production function 1.7, firm optimality condition 1.11, household budget constraint 1.24, goods market clearing condition 1.17, optimal consumption choice 1.18, optimal composition of labor margins 1.23 and optimal labor input condition 1.25.

Despite its relative parsimony, the model can not be solved analytically. The main results of the paper follow from the numerical solution of the full non-linear version of the model presented in this section. I use the analytical solution of the linearised version of the model to build the basic intuition behind the results in sections 1.3.5 and 1.5.

1.3.4 Aggregation and measuring productivity

Aggregate output and hours are defined as simple sums of aggregate variables

$$Y = \sum_{i=1}^{N} y_i, \tag{1.26}$$

$$H = \sum_{i=1}^{N} h_i. \tag{1.27}$$

Labor productivity is given by

$$LP = Y/H, \tag{1.28}$$

$$lp_i = y_i/h_i. \tag{1.29}$$

Since labor is the only production factor in our model, labor productivity equals measured total factor productivity according to the KLEMS methodology. I further refer to this measure as labor productivity or simply productivity. Since labor productivity in the data reflects variation in capital services and intermediate inputs, I consider measured total factor productivity to be the more suitable empirical counterpart, and use measured TFP in the numerical exercises.

1.3.5 Implications for cyclicality of productivity and flexibility of labor

In this section, I use the log-linearised version of the model in order to demonstrate that the cyclicality of measured aggregate productivity generated by my model depends both on the relative flexibility of hours and effort and on the relative importance of aggregate shocks to technology and demand. In what follows, I use the tilde symbol to denote the log-deviations of variables from their steady states.

Firstly, I illustrate how flexibility of hours and effort in my model influences the cyclicality of measured labor productivity, a mechanism similar to Galí and van Rens (2020). In log-deviations, production function 1.7 of industry i can be expressed as

$$\tilde{y}_i = \tilde{z}_i + (1-\alpha)\tilde{e}_i + (1-\alpha)\tilde{h}_i, \tag{1.30}$$

$$\tilde{lp}_i = \tilde{y}_i - \tilde{h}_i = \tilde{z}_i + (1-\alpha)\tilde{e}_i - \alpha\tilde{h}_i. \tag{1.31}$$

After a positive non-technology shock, the increased demand can only be satisfied by increasing labor input. In the case when hours are relatively flexible and effort is very rigid, i.e. close to the standard case with only one labor input margin, labor productivity falls due to diminishing returns to labor. On the contrary, if hours are very rigid and effort is relatively flexible, measured labor productivity increases with labor input due to the procyclical role of factor utilization. Expressing the optimal effort from the optimality condition 1.23 and plugging it into equations 1.30 and 1.31 gives

$$\tilde{y}_i = \tilde{z}_i + B\tilde{h}_i, \tag{1.32}$$

$$\tilde{lp}_i = \tilde{z}_i + \Gamma\tilde{h}_i, \tag{1.33}$$

where constants B and Γ are defined as

$$B = (1-\alpha)\left(1 + \frac{\eta}{1+\epsilon}\right), \tag{1.34}$$

$$\Gamma = -\alpha + (1-\alpha)\frac{\eta}{1+\epsilon}. \tag{1.35}$$

The response of output and productivity to an increase in hours depends on the degree of diminishing returns to labor α, and on the *elasticity ratio* $\frac{\eta}{1+\epsilon}$. Importantly, parameter Γ determines the response of productivity and can have both positive or negative values.

Let us first consider the implications of the extreme values of parameters η and ϵ. If ϵ is very high compared to η, effort is very rigid and $\frac{\eta}{1+\epsilon}$ goes to zero. In that case, the response of measured labor productivity to a change in hours is driven by the diminishing returns and Γ is negative. This might be the case if effort is very rigid ($\epsilon \to \infty$), or if hours are very elastic ($\eta \to 0$).

On the other hand, if η is very high in comparison to ϵ, adjusting hours is very costly in terms of utility. The optimizing households and firms choose to rely less on adjusting hours and more on adjusting effort. As a result, the observable labor input fluctuates less, but its correlation with measured labor productivity is positive. In fact, the coefficient Γ becomes positive for any $\frac{\eta}{1+\epsilon} > \frac{1}{2}$ in the case of the standard value of diminishing returns parameter $\alpha = 1/3$. To sum up, an increase in the relative flexibility of hours leads to a decrease in correlation between hours and measured productivity accompanied by an increase in relative volatility of hours.

Secondly, I discuss the role of the shock composition. Naturally, labor productivity in equation 1.33 positively depends on exogenous technology z_i. However, the reaction of hours to an improvement in technology can be both positive or negative, depending on the parameter values. Empirical estimates of the response of hours to technology improvements typically show that it is relatively small in absolute value and negative, both at the aggregate and industry level; see e.g. Galí (1999) and Holly and Petrella (2012).

Taking into account the empirical literature, the standard values of consumption elasticity ρ close to the log-utility case and the elasticity of substitution between goods of various industries σ close to one appear plausible. For σ close to one, the model generates small conditional volatility of industry hours and small (and possibly negative) covariance between industry hours and productivity. The same is true for the corresponding aggregate moments in the case when ρ is close to one. On the other hand, the previous paragraphs show that for a sufficiently high elasticity ratio $\frac{\eta}{1+\epsilon}$, the non-technology shocks in the model generate positive co-movement between hours and productivity. Therefore, a shift in the composition of shocks from demand to technology shocks may decrease the unconditional correlation.

Log-linearising the equations for aggregate output, hours, and labor productivity, it is straightforward to derive that

$$\tilde{LP} = \tilde{Y} - \tilde{H} \approxeq \tilde{Z} + \Gamma \tilde{H}, \tag{1.36}$$

where $\tilde{Z} = \frac{1}{N}\sum_{i=1}^{N} \tilde{z}_i$ is the average growth rate of the industry technology. Notice that equation 1.36 is analogous to industry-level equation 1.33. Thus, the relationship between aggregate labor productivity and hours depends on the parameters in a way that is similar to the industry-level variables.

1.3.6 Discussion

It is straightforward to relate my model to Galí and van Rens (2020), although there are several differences. Galí and van Rens interpret the measure of observable labor input in their model as employment, assuming fixed hours per worker. They also use a special case of the utility function featured in my model, with only one industry and linear disutility of working, the case analogous to $\eta = 0$. Thus, without any other frictions at work, households in Galí and van Rens would optimally choose constant effort and would always satisfy the changes in demand for labor by varying employment. Nevertheless, Galí and van Rens introduce quadratic hiring costs which ensure that workers' effort indeed varies over time. Their main exercise is to study the effect of the reduction of hiring costs on the cyclicality of labor productivity.

In order to keep the problem simple at the industry and aggregate level, I abstract from the hiring frictions and study the effect of varying the value of elasticity η. Both approaches generate changes in cyclicality of productivity through changing how flexibly observed labor input responds. In an alternative formulation of my model which also features quadratic costs of adjusting hours in a simple form, the close relationship between the two approaches is confirmed. The results are equivalent to the version presented in this paper, but the number of parameters that need to be identified increases and the formulas become more complicated.

1.4 Quantitative analysis

1.4.1 Model calibration

I simulate the model at quarterly frequency and calibrate the parameters accordingly. I subsequently convert the simulated series into annual frequency in order to obtain series which are comparable with the industry-level data set. The benchmark calibration targets selected second moments of the pre-1984 sample. I prefer to use the data moments computed using the growth rates of fixed-weight aggregate variables, as these offer the most relevant comparison to the model. The choice of aggregate series does not influence the main results. The benchmark calibration is summarized in table 1.7.

The model economy consists of $N = 77$ industries. Some of the model parameters are set to values that are standard in the macroeconomic literature. I set the curvature of production function α to 1/3 and assume log-utility of consumption $\rho = 1$.[9] The elasticity of substitution between industry goods σ is chosen quite arbitrarily at 0.9. Robustness checks show that the value of elasticity σ does not substantially influence the results. The elasticity of substitution affects the strength of the response of industry-level variables to industry-specific shocks. Thus, the main impact of choosing alternative values of σ is that it alters the size of industry-specific shocks in the model necessary to generate the fluctuations of industry variables with a realistic magnitude.

Utility function parameters λ_h and λ_e are scaling the model variables in a way that does not influence the results. I normalize λ_e such that there is unit effort in the steady state and choose λ_h to scale the size of steady state aggregate output. I calibrate the benchmark inverse elasticity of hours η to be at the lower end, but yet consistent with the values used in the macroeconomic literature. Macroeconomists typically focus on the elasticity of observed labor input with respect to wages, referred to as Frisch elasticity. In my model, Frisch elasticity depends on both parameters governing the flexibility of hours and effort and equals $\frac{1}{\eta}\left(1 + \frac{1}{\epsilon}\right)$. In line with the values used in contemporary DSGE models, I calibrate the Frisch elasticity to 0.5; see e.g. de Walque et al. (2015). For any given effort elasticity parameter ϵ, the Frisch elasticity pins down the value of hours elasticity parameter η.

The remaining preference parameter ϵ governs the elasticity of effort, thus pinning down the strength of the factor utilization channel in my model. Effort is typically not directly observed and I have little guidance from the literature concerning the value of the parameter. I calibrate ϵ jointly with the relative variance of aggregate demand shock σ_D^2 targeting two second moments from the pre-1984 sample: the relative volatility of hours with respect to output and the correlation of aggregate hours with measured TFP. The analysis in section 1.3.5 shows that the two parameters are well identified by the targets, as they have contrasting effects on the target values. A higher share of demand shocks increases both relative volatility of hours and, for elasticity ratio $\frac{\eta}{1+\epsilon}$

[9] I report the robustness exercises with respect to ρ, σ and Frisch elasticity of labor supply in Appendix 1.D.

Parameter	Symbol	Value	Source or target
Number of industries	N	77	data set, Jorgenson (2008)
Returns to labor	α	1/3	standard
Consumption elasticity	ρ	1	standard (robustness analysis)
Elasticity of substitution	σ	0.9	standard (robustness analysis)
Utility weight, hours	λ_h	3.7×10^{-4}	normalisation $Y^{ss} = 100$
Utility weight, effort	λ_e	1.5×10^{-3}	normalisation $e^{ss} = 1$
Hours elasticity	η	2.68	Frisch elasticity 0.5 (robustness)
Effort elasticity	ϵ	2.96	pre-1984 corr(TFP, H)
Variance agg. technology	σ_A^2		pre-1984 Var(VA)
Variance agg. demand	σ_D^2		pre-1984 ratio std$(H)/$ std(VA)
Variance ind. technology	σ_z^2		pre-1984 mean std$(tfp_i)/$ std(TFP)
Variance ind. demand	σ_v^2		pre-1984 mean std$(va_i)/$ std(VA)

Table 1.7: Benchmark calibration of the model parameters. The main exercise of this section is to vary the values of key parameters, depicted in bold font.

above a certain threshold, also the correlation of aggregate hours with productivity. A higher value of ϵ also increases the volatility of hours, as the agents rely more on adjusting hours and less on adjusting effort. However, a higher value of ϵ at the same time brings the correlation between aggregate hours and productivity down, due to a smaller contribution of pro-cyclical effort. Thus, conditional on other parameter values, there exists a unique pair of ϵ and σ_D matching both targets. The calibrated value of ϵ roughly equals 3 is in line with the values used in Galí and van Rens (2020) and Barnichon (2010).

Concerning the remaining shocks in the model, I calibrate their volatilities to roughly match the standard deviations of variables in the pre-1984 sample period. The volatility of aggregate technology shock σ_A is calibrated to match the volatility of aggregate output. The relative volatilities of industry specific shocks are set to match the standard deviation of industry-level fluctuations compared to the aggregate fluctuations in the pre-1984 period. Average (across industries) standard deviation of industry productivity relative to the aggregate productivity pins down σ_z. Average standard deviation of industry output relative to the aggregate output pins down σ_v. The shocks are not autocorrelated, although adding autocorrelation does not affect the results.

Table 1.8 shows the approximate variance decomposition of selected aggregate and industry-level variables simulated by the model. The benchmark calibration implies that the preference shock generates roughly 97% of the variance of the aggregate output and 29% of the variance of the aggregate productivity. The decompostion also shows that the aggregate shocks are relatively unimportant for the dynamics of the industry-level variables. Both aggregate shocks together explain about 12% of the variance of industry hours and output, and about 3% of the variance of industry productivity. Industry variables are mostly driven by the shocks affecting their own industry-specific conditions.

The main exercise for which I use the calibrated model is to vary the key parameter values in order to test the effects on the aggregate and industry-level moments. I vary the values of the following:

- Parameter η, which pins down the flexibility of hours. I change η from 2.7 to 1.8, such that

Variance decomposition	Aggregate shocks		Industry shocks	
	technology	demand	technology	demand
Aggregate variables				
Output	0.02	0.97	0.01	0.00
Productivity	0.43	0.29	0.28	0.00
Hours	0.00	1.00	0.00	0.00
Industry variables				
Output	0.00	0.11	0.10	0.79
Productivity	0.02	0.01	0.89	0.08
Hours	0.00	0.13	0.00	0.87

Table 1.8: Variance decomposition of the selected model variables. Approximate share of variance explained by each type of shock. For industry variables, the decomposition of the average variance is reported. Benchmark calibration.

the correlation of aggregate productivity with hours changes from the pre-1984 value (0.53) to the post-1984 value (-0.19). This corresponds to an increase in volatility of aggregate hours by roughly 30%. The experiment demonstrates the effect of increased flexibility of labor input in the period after 1984, and is roughly in line with the main exercise in Galí and van Rens (2020).

- Volatility of aggregate shock σ_D, such that the standard deviation of output changes from the pre-1984 value (0.028) to the post-1984 value (0.018). This corresponds to a change from aggregate demand shock explaining about 97% of the variance of output to explaining about 92%. The volatility σ_D decreases by around 42%, in line with the decrease identified in the literature; see e.g. Barnichon (2010).

1.4.2 Results

I solve the full non-linear model numerically and simulate the model economy for ten thousand periods in each of the exercises described below. I compute the second moments from the simulated series using the same detrending procedure as for the data.

The simulation results together with their data counterparts are summarized in tables 1.9 and 1.10. Top panel of table 1.9 displays again the key aggregate moments from the data for periods pre- and post-1984. The bottom panel of table 1.9 shows the corresponding aggregate moments generated by the model. The benchmark calibration matches the pre-1984 data moments very well, as three out of four moments are actually targeted in the calibration. The bottom panel of table 1.9 also reports the results for the two alternative parameter values: a lower value of η corresponding to a higher flexibility of hours, and a lower volatility of aggregate demand shock σ_D.

Change in flexibility of labor input

In the first exercise, I decrease η to two thirds of its benchmark value, such that the correlation of hours with productivity matches its post-1984 value of -0.19. This alternative calibration generates volatility of hours 30% higher and factor utilization volatility 13% smaller compared to the benchmark case. As expected, decreasing η leads to a simultaneous decrease in procyclicality

Aggregate	correlation productivity with output	with hours	rel. std.dev. hours	std.dev. output
Data				
Pre-1984	0.83	0.53	0.89	0.028
Post-1984	0.51	-0.19	1.20	0.018
Model				
Benchmark calibration	0.67	0.53	0.89	0.028
Flexible hours, $\eta = 1.8$	-0.05	-0.19	1.02	0.032
Smaller dem. shocks	0.59	0.34	0.85	0.018

Table 1.9: Selected aggregate second moments. Data (top panel) and model simulations (bottom panel).

Industry	correlation productivity with output	with hours	rel. std.dev. hours	std.dev. output
Data				
Pre-1984	0.81	0.00	0.63	0.080
Post-1984	0.79	-0.21	0.57	0.076
Model				
Benchmark calibration	0.59	0.30	0.85	0.083
Flexible hours, $\eta = 1.8$	0.18	-0.11	0.99	0.093
Smaller dem. shocks	0.59	0.28	0.84	0.079

Table 1.10: Selected averages of industry-level second moments. Data (top panel) and model simulations (bottom panel).

of aggregate productivity and an increase in relative volatility of hours, in line with the explanation proposed by Galí and van Rens (2020). The drop in the correlation of productivity with output overshoots its data counterpart, while the relative standard deviation of hours increases less in comparison to the data. Qualitatively, the model successfully replicates the post-1984 change in the aggregate moments.

However, table 1.10 reveals that the higher flexibility of hours generates counterfactual changes in the average industry-level moments. The model simulation results show that:

- average volatility of industry hours relative to industry output in the model increases compared to the benchmark case as much as for the aggregate hours. In the data, the industry-level relative standard deviation actually mildly decreased between the two time periods.
- average correlation of productivity with output in the model decreases substantially compared to the benchmark case. Whereas the decrease in correlation of industry variables generated by the model is somewhat smaller than for the aggregate variables, it is comparable in magnitude. In the data, the average industry-level correlation stayed virtually unchanged between the two sub-samples.
- average correlation of industry-level productivity with industry hours in the model decreases substantially. Whereas the decrease in correlation of industry variables generated by the model is somewhat smaller than for the aggregate variables, it is still twice as big as the change between the two sub-samples in the data.
- standard deviation of output at both industry and aggregate level in the model increases, as labor becomes more flexible. In the data, the period of Great Moderation is characterised

by a decrease in volatility of output.

The apparent problem with the change in flexibility of hours η is that it generates changes in second moments that are too similar at the aggregate and industry level. In section 1.5 I provide a detailed discussion of why this is the case.

Change in composition of aggregate shocks

Table 1.9 and table 1.10 also display the simulated moments for another alternative parameter value, a lower volatility of the aggregate demand shock. Several authors, for example Barnichon (2010) and Galí and Gambetti (2009), have suggested that the Great Moderation period after 1984 was characterised by a different composition of shocks, especially smaller demand side shocks, or muted effects of these shocks on the economy.

Recall that the benchmark calibration uses consumption elasticity ρ equals one, which implies that hours do not respond to the technology shocks. Thus, both technology and non-technology shocks generate a non-negative conditional correlation between hours and productivity. Consequently, as I further discuss in section 1.5, a change in the composition of shocks can decrease the correlation between productivity and hours, but can not reverse the sign of the correlation. Moreover, given the benchmark value of the elasticity ratio $\frac{\eta}{1+\epsilon}$, there is a positive lower bound on the correlation between productivity and output. For that reason, I can not use the negative aggregate correlation between productivity and hours in the post-1984 sample as the calibration target for this exercise. Instead, I choose to change the volatility of aggregate demand shock σ_D such that the model roughly matches the volatility of aggregate output in the post-1984 period. Such a decrease of σ_D is quantitatively similar to the exercise conducted in Barnichon (2010).

The alternative calibration changes the relative importance of the different types of shocks. The preference shock generates roughly 92% of the variance of aggregate output and 13% of the variance of aggregate productivity. The aggregate productivity is mostly explained by the aggregate technology shock (52% of variance) and the industry technology shocks (35%).

The last row of table 1.9 shows that the decrease in σ_D indeed drives the cyclicality of measured aggregate productivity down. Although the changes in aggregate correlations are smaller compared to the data, I argue that the results are sufficient in demonstrating the key insight of the paper. The changes in the composition of aggregate shocks may decrease the aggregate correlations, while keeping the industry-level moments virtually unchanged. The two types of shocks within my model are clearly too simple to reflect the whole extent of the structural changes happening during the Great Moderation period. However, the point of the exercise is to show that the composition of aggregate shocks has qualitatively very different effects on the aggregate and industry-level moments. The industry-level simulation results for the alternative value of σ_D are reported in the last row of table 1.10. The simulation results show that:

- average correlation of industry productivity with industry output in the model stays virtually unchanged, in line with the empirical evidence.
- average correlation of industry productivity with industry hours in the model stays unchanged, while in the data it slightly decreases.

- volatility of industry hours relative to industry output in the model stays virtually unchanged, in line with the empirical evidence.

  Notice that the model also predicts a small decrease in the relative volatility of aggregate hours. Changing the composition of shocks in my model does not explain the increase in the relative volatility. My results also in no way rule out the possibility that the increase in the relative volatility of aggregate hours was driven by the higher flexibility in the labor markets in the post-1984 period. I leave the question open for the ongoing research in the Great Moderation literature.

- standard deviation of output in the model decreases, as aggregate shocks in total become smaller, in line with the Great Moderation episode.

To summarize the main findings, both exercises (increasing the flexibility of hours and lowering the relative size of aggregate demand shocks) are able to qualitatively replicate the decrease in the procyclicality of aggregate productivity within my model framework. However, the change in the relative size of shocks appears to be more successful in simultaneously replicating the second moments at the industry level. The next section explains the intuition behind the results based on the analytical formulas derived for the industry and aggregate second moments.

1.5 Analytical insights

In this section, I use the log-linearised model equations in order to build the intuition behind the main results presented in section 1.4.2. I discuss the impact of the relative flexibility of hours and effort and the impact of the relative importance of aggregate shocks to technology and demand on the second moments using suitable special cases. I explain why the two mechanisms differ in their implications for the industry-level moments. I follow the same notation as in the previous sections and use the tilde symbol to denote the log-deviations of variables from their steady states.

Recall that equations 1.32 and 1.33 state that

$$\tilde{y}_i = \tilde{z}_i + B\tilde{h}_i,$$

$$\tilde{lp}_i = \tilde{z}_i + \Gamma\tilde{h}_i,$$

where constants B and Γ are defined as

$$B = (1-\alpha)\left(1 + \frac{\eta}{1+\epsilon}\right),$$

$$\Gamma = -\alpha + (1-\alpha)\frac{\eta}{1+\epsilon}.$$

Coefficients B and Γ determine the response of output and productivity, respectively, to an increase in hours. Moreover, for the aggregate variables it holds that

$$\tilde{Y} \approxeq \tilde{Z} + B\tilde{H},$$

$$\tilde{LP} \approxeq \tilde{Z} + \Gamma\tilde{H},$$

where $\tilde{Z} = \frac{1}{N}\sum_{i=1}^{N} \tilde{z}_i$ is the average growth rate of the industry technology.

Using these equations it is straightforward to derive the approximate expressions for the key aggregate and industry-level variances and correlations in the model. In the next section, I use these expressions in order to build the intuition behind the key model properties reported in section 1.4.2.

1.5.1 Relative volatility of hours

Property 1 *Within the model environment, both a change in the relative flexibility of hours and effort and a change in the relative composition of aggregate shocks can generate a variation in the relative volatility of aggregate hours. However, an increase in the relative flexibility of hours also necessarily increases the relative volatility of hours at the level of individual industries, while a change in the composition of aggregate shocks does not.*

The relative variance of industry hours and output in my model after detrending can be expressed as

$$\frac{\operatorname{Var}(\tilde{h}_i)}{\operatorname{Var}(\tilde{y}_i)} = \frac{\operatorname{Var}(\tilde{h}_i)}{\operatorname{Var}(\tilde{z}_i) + B^2 \operatorname{Var}(\tilde{h}_i) + 2B \operatorname{Cov}(\tilde{z}_i, \tilde{h}_i)}. \tag{1.37}$$

Recall that in the case when the elasticity of substitution σ equals one, labor input does not respond to changes in industry technology and the covariance between $\tilde{z}_i$ and $\tilde{h}_i$ is zero. In that case, we can rewrite the previous equation as

$$\frac{\operatorname{Var}(\tilde{h}_i)}{\operatorname{Var}(\tilde{y}_i)} = \frac{1}{\frac{\operatorname{Var}(\tilde{z}_i)}{\operatorname{Var}(\tilde{h}_i)} + B^2}. \tag{1.38}$$

Equation 1.38 expresses the relative volatility of hours in terms of two factors: the parameter B, and the relative variance of industry technology $\tilde{z}_i$ and hours $\tilde{h}_i$.[10]

I first discuss the role of the relative size of aggregate shocks. In equation 1.38, exogenous shocks only influence term $\frac{\operatorname{Var}(\tilde{z}_i)}{\operatorname{Var}(\tilde{h}_i)}$. While the numerator $\operatorname{Var}(\tilde{z}_i)$ only reflects the shocks to technology, the denominator only reflects the shocks to demand in the case when σ is one. An increase in the relative variance of technology shocks $\tilde{z}_i$ decreases the relative variance of industry hours and output.

Recall that equation 1.9 states that the industry technology depends on an aggregate and an idiosyncratic industry-specific component, $\tilde{z}_i = \tilde{A} + \tilde{\tilde{z}}_i$. Industry demand also depends on an aggregate component (preference shock D) and an idiosyncratic component (stochastic weight v_i). The key piece of intuition is the property that the aggregate shocks explain a minor part of the fluctuations of industry-level variables, while the idiosyncratic component explains the major part, see section 1.4.1. In other words, industry-level variables are mostly driven by shocks specific to the own industry. This property is a typical result in the literature on industry business cycles; see e.g. Horvath (2000), Acemoglu et al. (2012). Because aggregate technology and demand shocks explain a very small fraction of the variance of industry variables $\tilde{z}_i$ and $\tilde{h}_i$, a change in their

[10] The robustness exercise in Appendix 1.D shows that the non-zero covariance term arising from choosing the value of $\sigma \neq 1$ does not substantially alter the result.

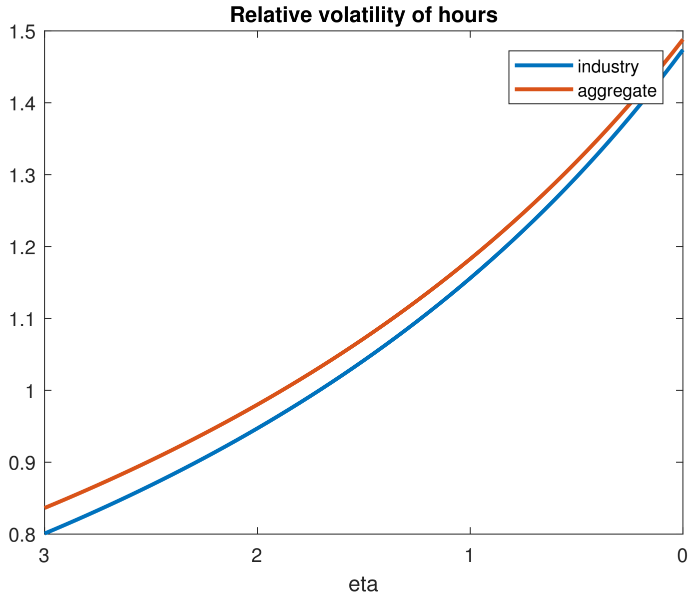

Figure 1.3: Comparison between the aggregate and industry relative volatility of hours (y-axis) for varying elasticity of hours η (x-axis). Benchmark calibration.

relative importance has a very limited effect on the term $\frac{\text{Var}(\tilde{z}_i)}{\text{Var}(\tilde{h}_i)}$, and does not change the relative volatility of industry hours significantly.

On the other hand, a change in the elasticity ratio $\frac{\eta}{1+\epsilon}$ influences both terms in the denominator on the right hand side of equation 1.38. In the case of very rigid hours, when $\frac{\eta}{1+\epsilon}$ goes to infinity, both terms in the denominator go to infinity. Thus, the relative variance of hours goes to zero. In contrast to a change in the relative size of aggregate shocks, a change in the relative flexibility of hours and effort generates a substantial change in the relative volatility of industry hours.

The relative variance of aggregate hours and output can be derived analogously to equation 1.38. Recall that in the case when CRRA utility parameter ρ equals one, the covariance between technology $\tilde{Z}$ and hours $\tilde{H}$ is again zero. In that case we get

$$\frac{\text{Var}(\tilde{H})}{\text{Var}(\tilde{Y})} \approx \frac{1}{\frac{\text{Var}(\tilde{Z})}{\text{Var}(\tilde{H})} + B^2}, \tag{1.39}$$

where the approximation sign reflects the approximate relation in equation 1.36.[11] A comparison of equations 1.38 and 1.39 delivers the two main insights of the exercise.

Firstly, in contrast to the industry level, a change in the relative size of aggregate shocks may change the relative volatility of aggregate hours. The key difference in comparison to the industry volatility is that the aggregate shocks explain a large part of the fluctuations of aggregate macroeconomic variables. The idiosyncratic industry shocks on average cancel out to a large extent and are less important in the aggregate. Thus, the relative variance of average technology level $\tilde{Z}$ and aggregate hours $\tilde{H}$ is more strongly affected by changes in the relative importance of aggregate technology and demand shocks.

[11]The robustness exercise in Appendix 1.D shows that the non-zero covariance term arising from choosing the value of $\rho \neq 1$ does not substantially alter the result.

Secondly, the similarity between equations 1.38 and 1.39 reveals that a change in the elasticity ratio $\frac{\eta}{1+\epsilon}$ influences the relative variance of hours at the aggregate and industry level in an analogous way. The only difference between the two expressions is the effect on the relative variance terms $\frac{\mathrm{Var}(\tilde{z}_i)}{\mathrm{Var}(\tilde{h}_i)}$, resp. $\frac{\mathrm{Var}(\tilde{Z})}{\mathrm{Var}(\tilde{H})}$, but the contribution of these terms occurs to be relatively small. Figure 1.3 plots the comparison between the aggregate and industry-level relative volatility of hours for the benchmark model calibration, varying the value of utility parameter η which pins down the flexibility of hours. The figure illustrates that changes in η generate changes in the relative volatility of hours at the aggregate and industry level that are quite similar in magnitude.

1.5.2 Correlation between productivity and hours

Property 2 *Within the model environment, both a change in the relative flexibility of hours and effort and a change in the relative composition of aggregate shocks can generate changes in the aggregate correlations qualitatively in line with the empirical evidence. However, an increase in the relative flexibility of hours also necessarily decreases the correlations between productivity and hours (resp. output) at the level of individual industries, while a change in the composition of aggregate shocks does not.*

In this section I focus on deriving the properties of the correlation between measured productivity and hours, using equation 1.33. Appendix 1.E.1 shows the derivations for the correlation between measured productivity and output and discusses the analogous properties.

At the industry level, the correlation between measured productivity and hours can be expressed as

$$\mathrm{Corr}(\tilde{lp}_i, \tilde{h}_i) = \frac{\frac{\mathrm{Cov}(\tilde{z}_i, \tilde{h}_i)}{\mathrm{Var}(\tilde{h}_i)} + \Gamma}{\sqrt{\frac{\mathrm{Var}(\tilde{z}_i)}{\mathrm{Var}(\tilde{h}_i)} + \Gamma^2 + 2\Gamma\frac{\mathrm{Cov}(\tilde{z}_i, \tilde{h}_i)}{\mathrm{Var}(\tilde{h}_i)}}}. \tag{1.40}$$

In the case when the elasticity of substitution σ equals one, the covariance between industry technology and hours is zero. In that case, I obtain

$$\mathrm{Corr}(\tilde{lp}_i, \tilde{h}_i) = \frac{\Gamma}{\sqrt{\frac{\mathrm{Var}(\tilde{z}_i)}{\mathrm{Var}(\tilde{h}_i)} + \Gamma^2}}. \tag{1.41}$$

Equation 1.41 expresses the correlation in terms of two factors: the parameter Γ, and the relative variance of industry technology $\tilde{z}_i$ and hours $\tilde{h}_i$.

Again, I first discuss the role of the relative size of aggregate shocks. In equation 1.41, the exogenous shocks only influence term $\frac{\mathrm{Var}(\tilde{z}_i)}{\mathrm{Var}(\tilde{h}_i)}$. An increase in the relative size of technology shock z_i decreases the absolute value of the correlation, but does not reverse its sign. As discussed in detail above, a change in the relative size of the aggregate technology and demand shocks can not generate a big change in the term $\frac{\mathrm{Var}(\tilde{z}_i)}{\mathrm{Var}(\tilde{h}_i)}$. The reason is that the aggregate shocks only explain a small part of the variance of industry-level variables.

To the contrary, a change in the elasticity ratio $\frac{\eta}{1+\epsilon}$ influences all terms on the right hand side of equation 1.41. Coefficient Γ defined in equation 1.35 determines the sign of the correlation. In

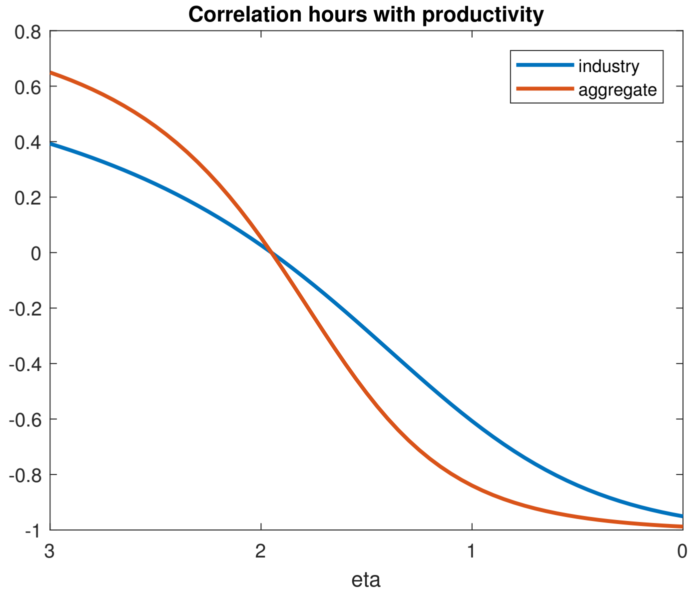

Figure 1.4: Comparison between the aggregate and industry correlation between labor productivity and hours (y-axis) for varying elasticity of hours η (x-axis). Benchmark calibration.

the case of very flexible hours, the elasticity ratio goes to zero and Γ is negative. In the case when hours are extremely rigid, the elasticity ratio goes to infinity and the correlation approaches one.

The correlation between aggregate productivity and hours can be derived analogously to equation 1.41. In the case when the utility parameter ρ is equal to one, the covariance between technology $\tilde{Z}$ and hours $\tilde{H}$ is zero and I get

$$\mathrm{Corr}(\tilde{LP}, \tilde{H}) = \frac{\Gamma}{\sqrt{\frac{\mathrm{Var}(\tilde{Z})}{\mathrm{Var}(\tilde{H})} + \Gamma^2}}. \tag{1.42}$$

The comparison of equations 1.41 and 1.42 delivers another two insights which are key for the results of this paper.

Firstly, a change in the relative size of aggregate technology and demand shocks can generate a change in the correlation between productivity and hours at the aggregate level, but not at the industry level. The key difference between the aggregate and the industry level is again that the aggregate shocks explain a substantial part of the variance of the aggregate variables, but only a minor part of the industry variables. Thus, the relative variance of average technology level $\tilde{Z}$ and aggregate hours $\tilde{H}$ is strongly affected by the relative importance of aggregate technology and demand shocks, while the relative variance of industry technology $\tilde{z}_i$ and industry hours $\tilde{h}_i$ is not.

Secondly, a change in the elasticity ratio $\frac{\eta}{1+\epsilon}$ influences the correlation at the aggregate and industry level in an analogous way. The only difference between the two expressions is the relative variance term $\frac{\mathrm{Var}(\tilde{z}_i)}{\mathrm{Var}(\tilde{h}_i)}$, resp. $\frac{\mathrm{Var}(\tilde{Z})}{\mathrm{Var}(\tilde{H})}$, but the contribution of this term occurs to be rather small. Figure 1.4 plots the comparison between aggregate and industry-level correlations for the benchmark calibration, varying the value of parameter η that pins down the flexibility of hours. The figure shows that changes in parameter η generate changes in the correlation between productivity and hours at the aggregate and industry level that are similar in magnitude.

	Benchmark calibration	Higher flexibility of hours	Lower variance demand shock
corr($*$, VA)			
Technology Z	0.17	0.15	0.33
Utilization-adjusted productivity	-0.76	-0.84	-0.36
Utilization component	0.99	0.99	0.95
corr($*$, H)			
Technology Z	0	0	0
Utilization-adjusted productivity	-0.86	-0.91	-0.65
Utilization component	1	1	1
Relative volatility			
std(Utilization)/std(Adj. prod.)	1.2	0.8	0.6
std(Utilization)/std(Technology)	2.3	2.0	1.2

Table 1.11: Decomposition of the measured productivity into factor utilization component and utilization-adjusted productivity. Simulated series with benchmark calibration and two alternative calibrations: higher flexibility of hours and lower variance of demand shock.

To summarize the key intuition provided in this section, an increase in the relative flexibility of observable labor supply margin within my model leads to a decrease in procyclicality of measured aggregate productivity in line with the literature. However, it also generates a decrease (of a comparable magnitude) in the industry-level correlations, which is not in line with the empirical evidence. On the contrary, a change in the relative variance of technology and non-technology aggregate shocks generates a change in the aggregate correlations while the industry-level correlations stay unaffected.

1.6 Role of factor utilization

Fernald and Wang (2016) make a handful of important observations about the nature of the change in cyclicality of productivity, see section 1.1.1. Given that these observations are an important piece of evidence helping to discriminate between various explanations suggested in the literature, I briefly discuss how the two mechanisms in my model are able to replicate these observations. I decompose the measured productivity in my model to the factor utilization component and the utilization-adjusted measured productivity and report the moments for the pre- and post-1984 period in table 1.11. Notice that the utilization-adjusted productivity in my model again consists of two components: the average technology level Z and the effect of diminishing returns to labor. Table 1.11 also reports the moments for the isolated technology component Z.

The decomposition of the model variables confirms that both mechanisms comply with the observations from Fernald and Wang (2016). Firstly, utilization-adjusted TFP was never really pro-cyclical before the mid-1980s, and the correlation with inputs and output weakly increased after the mid-1980s. All three calibrations of my model generate countercyclical utility-adjusted productivity. The reason is that the main driving force of the fluctuations in aggregate output and hours is the aggregate demand shock, thus the effect of diminishing returns to labor dominates the true productivity changes. Lower volatility σ_D generates slightly higher correlations, because the relative importance of the procyclical technology shocks increases. Secondly, factor utilization was the procyclical component of measured productivity before the mid-1980s and it stayed procyclical.[12] The model generates very high correlations of the utilization component with output and hours. Third, the relative volatility of the factor utilization compared to the utilization-adjusted productivity substantially decreased in the period after 1984. The major part of the vanishing cyclicality of measured productivity is explained by the decrease in the volatility of the utilization component. Both alternative choices of model parameters, reported in the second and third column of table 1.11, deliver a significant decrease in the relative volatility of the utilization component compared to the benchmark calibration. For more flexible hours, the utilization component becomes less volatile as firms and households adjust hours more easily and rely less on adjusting effort. In the case of lower volatility of demand shocks, the fluctuations of utilization component decrease together with the fluctuations of hours, which increases the relative importance of the utilization-adjusted component.

1.7 Conclusions

In this paper I contribute to the discussion on the vanishing cyclicality of aggregate productivity by bringing in the industry-level evidence, which can help to discriminate between various explanations proposed in the literature. I first document the change in cyclical properties of productivity in the U.S. using industry-level data. I focus on a puzzling feature that the correlations of industry productivity with industry output and labor input remained on average much more stable before and after the mid-1980s compared to the aggregate correlations. The cyclical correlations of productivity decreased at the aggregate level, but much less at the industry level.

I construct a simple industry-level RBC model that can generate changes in the cyclical co-movement of measured aggregate productivity and other macroeconomic variables through two distinct mechanisms. The procyclicality of aggregate productivity in the model, measured in terms of correlations with labor input and output, decreases when the relative size of aggregate demand side shocks decreases compared to technology shocks, as suggested, for example, in Barnichon (2010). The procyclicality of aggregate productivity also decreases when the observed labor input (hours) becomes more flexible in comparison to the unobserved labor input margin (effort), as suggested in Galí and van Rens (2020). I choose these two mechanisms from a wide variety of explanations proposed in the literature as the most likely candidates after considering the existing empirical evidence; e.g. Fernald and Wang (2016).

Although both mechanisms are able to reduce the correlations of aggregate productivity with output and labor input, I show that they have qualitatively different predictions for the cyclical properties of industry-level variables. Within my model framework, only the mechanism based on a structural change in the composition of aggregate shocks is able to generate changes in aggregate correlations without generating counterfactual changes at the industry level.

However, a change in the composition of the two aggregate shocks in my model can generate only a part of the decrease in cyclicality of aggregate productivity observed in the data. The model with two types of aggregate shocks and no frictions is clearly too stylized to reflect the whole extent of the structural changes happening in the U.S. in the mid-1980s. The contribution

[12]The correlation of the utilization measure with labor input actually decreased for brief periods between 1990 and 2005, but the effect is less important than the drop in the volatility of factor utilization.

of this paper is mainly in providing the intuition for why and how aggregate shocks can influence the moments at the aggregate and industry level in a different way. The simple model framework in this paper is suitable for this purpose. Nevertheless, such model has a limited ability to match the moments for the two subperiods.

For a better fit of various pre- and post-1984 moments, and in order to answer the question of what kind of aggregate shocks are responsible for the changes in dynamic properties of productivity, a more complex model environment is necessary. The shocks in the model should be selected and calibrated such that they resemble the properties of the disturbances identified in the empirical studies. Ideally, such a model should feature a more realistic industry structure, but also dynamic decisions and nominal rigidities, which are important factors influencing the propagation of shocks across industries.

In addition to bringing a new piece of evidence to the rich literature on the vanishing cyclicality of labor productivity, I view a secondary contribution of the paper as a means of promoting the use of disaggregated data sets in macroeconomic research. The broadening gap between the available disaggregated data and the aggregate *macro* perspective offers new opportunities and challenges for researchers in the era of big data. Before all else, new and growing industry-level data sources such as the World Input-Output Database should be exploited more extensively to test existing macroeconomic theories.

Appendix 1

1.A Data and construction of the moments

The primary data source that I use is the KLEMS growth accounting data set developed by Dale Jorgenson and his co-authors (Jorgenson 2008). The data set provides annual information on capital, labor and intermediate inputs and outputs of the U.S. economy between 1960 and 2005, disaggregated into 88 industries. This appendix describes in detail the construction of data series, aggregates, and data moments.

In line with the literature, I focus on the private business sector which consists of 77 industries. I aggregate the industry-level series of the private business sector to obtain the aggregate series. I exclude all government industries and the *Private households* industry. Government industries are usually omitted from productivity exercises because market prices are not available for government industries and are set arbitrarily. In my data, an additional problem with the government industries is that the information about intermediate inputs is often missing. In one case, a private industry (*59 Real estate - owner occupied dwellings*) does not utilize all inputs, as the only input is capital.

Table 1.12 lists the private sector industries and their relative shares in nominal output.

List of industries, private business sector, part 1			
		gross output nominal share	value added nominal share
1	Farms	2.48	2.43
2	Agricultural services, forestry	0.37	0.35
3	Fishing	0.12	0.12
4	Metal mining	0.12	0.14
5	Nonmetal mining	0.15	0.21
6	Coal mining	0.26	0.39
7	Oil and gas extraction	1.52	1.90
8	Construction	7.04	6.65
9	Lumber and wood	0.89	0.69
10	Furniture and fixtures	0.53	0.49
11	Nonmetallic mineral products	0.76	0.83
12	Primary metals	1.68	1.39
13	Fabricated metal production	1.91	1.94
14	Machinery excl. computers	2.17	2.33
15	Computers and office equipment	0.76	0.45
16	Insulated wire	0.21	0.23
17	Audio and video equipment	0.12	0.09
18	Other electrical machinery	0.73	0.78
19	Communications equipment	0.46	0.45
20	Electronic components	0.78	0.61
21	Motor vehicles	2.64	1.22
22	Aerospace	1.13	1.22
23	Ships and boats	0.17	0.22
24	Other transportation equipment	0.17	0.15
25	Measuring instruments	0.62	0.67
26	Medical equipment and opthalmic goods	0.39	0.32
27	Other instruments	0.21	0.28
28	Misc. manufacturing	0.41	0.43
29	Food	3.99	2.33
30	Tobacco	0.23	0.19
31	Textile	0.70	0.63
32	Apparel	0.65	0.73
33	Leather	0.11	0.16
34	Paper and allied	1.28	1.05
35	Publishing	0.88	0.98
36	Printing and reproduction	0.68	0.72
37	Chemicals excl. drugs	2.39	1.98
38	Drugs	0.65	0.54
39	Petroleum and coal products	1.83	0.54
40	Rubber and misc. plastics	1.10	0.86

List of industries, private business sector, part 2			
		gross output nominal share	value added nominal share
41	Railroad transportation	0.43	0.75
42	Local passenger transit	0.22	0.40
43	Trucking and warehousing	1.75	1.83
44	Water transportation	0.34	0.34
45	Air transportation	0.83	0.67
46	Transportation services and pipelines	0.31	0.30
47	Telephone and telegraph	2.04	2.14
48	Radio and TV	0.53	0.39
49	Electric utilities (pvt)	2.05	2.28
50	Gas utilities	0.68	0.38
51	Water and sanitation	0.18	0.12
52	Wholesale trade	5.46	6.64
53	Retail trade excl. motor vehicles	4.40	5.78
54	Retail trade, motor vehicles	1.20	1.45
55	Eating and drinking	2.06	1.79
56	Depository institutions	2.74	2.40
57	Nondeposit; Sec-com brokers; Investment	1.76	1.51
58	Insurance carriers, agents, services	2.23	1.89
59	Real Estate - owner occupied	2.71	5.11
60	Real Estate - other	5.63	7.79
61	Hotels	0.77	0.88
62	Personal services	0.72	0.73
63	Business services excl. computer	2.48	2.70
64	Computer services	1.27	0.89
65	Auto services	1.01	0.86
66	Misc. repair services	0.42	0.58
67	Motion pictures	0.40	0.29
68	Recreation services	0.80	0.70
69	Offices of health practitioners	2.12	2.20
70	Nursing and personal care facilities	0.46	0.43
71	Hospitals, private	2.00	1.87
72	Health services, nec	0.53	0.47
73	Legal services	1.06	1.12
74	Educational services (private)	0.81	0.78
75	Social services and membership org.	1.49	1.34
76	Research	0.42	0.37
77	Misc professional services	2.38	2.11

Table 1.12: List of private industries, Jorgenson and coauthors. Percentage shares of industry nominal gross output and value added in total gross output and value added, average for 1960-2005.

1.A.1 Data inputs

Gross output

Jorgenson database reports industry nominal gross output and producers price indexes normalized in 1996. Therefore, I express real gross output (and other real variables) in 1996 dollars. Aggregate real gross output is defined as the sum of real outputs across the 77 industries of the private business sector.

Intermediate inputs

Real volumes of intermediate inputs can be expressed in 1996 dollars using the reported purchasers price index. I use Fisher price index in order to aggregate the real intermediate inputs delivered to a particular industry. This approach is consistent with the model economy, where the variety of intermediate inputs $m_{j,i,t}$ is aggregated into input $M_{i,t}$ according to a CES function.

Notice that gross output and intermediate input goods are not counted in consistent real units, as the two price indexes differ. Moreover, intermediate inputs reported in the database include imports, but the information about exports is not available. For these reasons, the goods market clearing identity at the industry level does not hold.

$$\text{gross output} \neq \text{consumption} + \text{investment} + \text{intermediate inputs}$$

The discrepancy is important for several reasons. First, value added can not be computed as a simple difference between gross output and intermediate inputs. Second, as we will see later, the measures of productivity are not comparable across industries.

Labor input

The measure of labor input reported in the Jorgenson data set is effective hours. Effective hours are defined as total hours adjusted for the composition of workforce, taking into account basic observable characteristics (education, age and gender).

The Jorgenson database reports nominal costs of effective labor and a price index for each industry, which allow to compute the real labor input series. However, the units are not comparable across industries. For the sake of easier interpretation, I rescale the real labor input series to approximately reflect effective hours worked in each industry. I use the 72-industry version of EU KLEMS data (based on SIC classification of industries) as an additional data source in order to pin down the effective hours and hourly wages in each industry in 1996. I apply these wages to the labor costs information in the Jorgenson data set in order to express the real labor input in hours. The rescaling of labor input series does not affect the results, but has the advantage that it allows me to define aggregate hours as a sum of industry hours.

Although the two data sets are based on the same accounting principles, there are several issues with matching the EU KLEMS to Jorgenson KLEMS. I resolve these issues using ad-hoc rules which try to minimize the effect of the discrepancies.

- The level of disaggregation in some cases differs between the two datasets. In case several Jorgenson industries constitute a single EU KLEMS industry, I used the same wage level for all the industries. In one case a Jorgenson industry (*63 Business services excluding computer services*) corresponds to two EU KLEMS industries. I approximated the wage in this industry by a weighted average of wages in both the EU KLEMS industries. Some EU KLEMS service industries include both private and government sector, while I only focus on the private sector in the Jorgenson data. It is likely that the wages in the private and government sector differ, however, a large discrepancy is rather unlikely. In this case, I consider the wages reported in the EU KLEMS data set to apply for the private-sector industries in the Jorgenson data. In one case (*51 Water and sanitation*) the labor compensation and hours data in the EU KLEMS are missing. I use the wage information from the *50 Gas utilities* industry, which I consider to be the closest approximation.
- I chose 1996 as the base year for pinning down the industry-level wages in the EU KLEMS data. The results are robust with respect to the choice of base year.

Capital accounts

Measuring the capital stock and capital services is typically the most challenging part of the growth accounting. Jorgenson database provides the nominal values and price index for the capital services in each industry. The KLEMS growth accounting is based on the assumption of perfect competition and zero profits. However, the nominal value of capital services is identified as the residual between value added and labor compensation. Therefore, it includes both the user cost of capital and profits.

The model abstracts from endogenous capital and assigns the non-labor income exclusively to firm profits. Since labor productivity is potentially affected by the fluctuations in capital services, it is more suitable to compare the model outcomes with measured total factor productivity.

Value added

Because the data set does not allow to compute outputs and intermediate inputs in consistent real units, I can not compute industry real value added as a simple difference between the two series. I thus follow the standard growth accounting methodology and define real value added using the so-called double deflation method (Timmer et al. 2007a). The method provides growth rates series of value added for each industry. Nevertheless, it does not provide level series in units that are consistent across industries. I define aggregate real value added as aggregate nominal value added divided by the Fisher price index associated with the industry-level prices.

1.A.2 Measuring productivity

I rely on the standard KLEMS methodology (Timmer et al. 2007b) for computing the two standard measures of productivity: labor productivity and TFP. I define the measured labor productivity as value added per effective hour and measured TFP as the standard Solow residual.

Industry accounts of the KLEMS type are based on the assumptions of perfectly measurable factor inputs, constant returns to scale and perfect competition, such that the factors are paid their marginal products. In the model, however, firms make profits, there are diminishing returns, and factor utilization is not measurable. Therefore, the standard Solow residual formulas used in productivity accounting deviate from the true technology in the model. Measured TFP is influenced not only by technology shocks, but also by changes in demand. At industry level, I compute the Solow residuals following the methodology of the EU KLEMS database as

$$\hat{TFPm}_{it} = \hat{va}_{it} - s^L_{it}\hat{h}_{it} - s^K_{it}\hat{k}_{it}, \tag{1.43}$$

where s^X is the cost share of input X in total production costs and hats denote growth rates of variables. I refer to $TFPm$ as *measured productivity.* I choose to report value added-based TFP over gross output-based TFP at both aggregate and industry level because they are directly comparable with their model counterparts. The difference between the two measures is only in rescaling the productivity series by the share of cost share of value added in the gross output.[13]

The true technology in my model can be expressed as

$$\hat{A_t z_{it}} = \hat{va}_{it} - \frac{p_i y_i - d_i}{p_i y_i}\left(s^L_{it}(\hat{h}_{it} + \hat{e}_{it}) - s^K_{it}\hat{k}_{it}\right), \tag{1.44}$$

where the last term drops out in case of constant capital input. True technology is only equivalent to measured productivity (eq. 1.43) in the case of constant effort and constant returns to scale.

Moreover, the levels of measured productivity are not comparable across industries, as value added and inputs are not counted in consistent units. In line with the KLEMS methodology, I define *measured aggregate TFP* using aggregate measures of inputs and output as

$$\hat{TFPm}_t = \hat{VA} - s^H_t\hat{H}_t - s^K_t\hat{K}_t. \tag{1.45}$$

For all variables I always use the same procedure to construct them in the data and from the model simulations.

1.A.3 Moments

Correlations between productivity and other aggregate variables and their standard deviations are computed using the series described in the main text. Cross-industry weighted averages of industry-level correlations and standard deviations are computed using nominal output shares as weights. The benchmark weighting is based on the industries' average nominal output share in the first sub-period. I compute the cross-industry second moments using alternative weights in order to check the robustness of the results.

Standard deviation of measured value added and productivity in two of the industries in the data sample is extremely volatile. Both industries (*39 Petroleum and coal products* and *50 Gas utilities*) are likely to be affected by extremely volatile prices of their intermediate inputs, especially in the first sub-period. Because these extreme values affect the averages disproportionally and

[13] $\hat{TFPm}_{it} = \hat{va}_{it} - s^K_{it}\hat{k}_{it} - s^L_{it}\hat{h}_{it} = \frac{1}{s^{VA}_{it}}\left(\hat{y}_{it} - \bar{s}^K_{it}\hat{k}_{it} - \bar{s}^L_{it}\hat{h}_{it} - \bar{s}^M_{it}\hat{M}_{it}\right) = \frac{1}{\bar{s}^{VA}_{it}}\hat{TFPm}^{GO}_{it}$

can not be captured by the model with ex ante homogeneous industries, I winsorize the standard deviations at the maximum value across the remaining industries for each of the variables.

1.B Additional empirical evidence

1.B.1 Comparison to previous studies

Table 3a. Cyclical correlation between labor productivity and output (VA): 1950–2007

Filter	1950 - 2007	1950 - 1983	1984 - 2007	Subperiod Diff.
Bandpass	0.350	0.428	0.042	-0.386
CF	0.399	0.430	0.294	-0.136
HP	0.316	0.420	-0.092	-0.512
First Difference	0.561	0.64	0.168	-0.472

Table 4a. Cyclical correlation between TFP and output (VA): 1950–2007

Filter	1950 - 2007	1950 - 1983	1984 - 2007	Subperiod Diff.
Bandpass	0.763	0.810	0.488	-0.322
CF	0.793	0.818	0.684	-0.134
HP	0.746	0.805	0.402	-0.403
First Difference	0.826	0.874	0.482	-0.392

Figure 1.5: Aggregate correlations pre- and post-1984 in Wang (2014).

Table 1. The Vanishing Procyclicality of Labor Productivity

	Corr with output			Corr with labor input		
	Pre-84	Post-85	Change	Pre-84	Post-85	Change
Output per hour						
BP	0.63	0.07	−0.55	0.23	−0.41	−0.64
	[0.05]	[0.08]	[0.10]	[0.08]	[0.07]	[0.11]
4D	0.65	0.18	−0.47	0.18	−0.42	−0.60
	[0.05]	[0.09]	[0.10]	[0.07]	[0.09]	[0.11]
HP	0.64	−0.09	−0.72	0.21	−0.55	−0.77
	[0.05]	[0.09]	[0.10]	[0.07]	[0.07]	[0.10]
Output per worker						
BP	0.78	0.51	−0.27	0.29	−0.11	−0.39
	[0.03]	[0.07]	[0.07]	[0.08]	[0.09]	[0.12]
4D	0.77	0.44	−0.33	0.19	−0.20	−0.40
	[0.03]	[0.08]	[0.08]	[0.07]	[0.12]	[0.14]
HP	0.77	0.32	−0.45	0.24	−0.29	−0.53
	[0.03]	[0.09]	[0.09]	[0.07]	[0.09]	[0.11]

Table 2. The Rising Volatility of Labor Input

	Std. Dev.			Relative Std. Dev.		
	Pre-84	Post-85	Ratio	Pre-84	Post-85	Ratio
Hours (private sector)						
BP	2.02	1.52	0.75	0.80	1.09	1.37
	[0.10]	[0.09]	[0.06]	[0.03]	[0.04]	[0.07]
4D	3.05	2.43	0.80	0.77	1.08	1.40
	[0.16]	[0.27]	[0.10]	[0.03]	[0.06]	[0.10]
HP	2.04	1.76	0.86	0.79	1.20	1.52
	[0.10]	[0.10]	[0.07]	[0.03]	[0.05]	[0.09]
Employment (private sector)						
BP	1.66	1.20	0.72	0.66	0.87	1.32
	[0.08]	[0.07]	[0.06]	[0.03]	[0.05]	[0.09]
4D	2.58	2.06	0.80	0.65	0.92	1.41
	[0.13]	[0.23]	[0.10]	[0.03]	[0.06]	[0.11]
HP	1.72	1.46	0.85	0.66	0.99	1.50
	[0.09]	[0.08]	[0.07]	[0.03]	[0.06]	[0.11]

Figure 1.6: Aggregate correlations and volatility pre- and post-1984 in Galí and van Rens (2020).

1.B.2 Robustness of industry-level correlations

	1960-2005	1960-1983	1984-2005	Difference
corr(TFP, GDP)				
First Diff.	0.80	0.81	0.79	-0.02
	[0.02]	[0.01]	[0.03]	[0.04]
CF	0.82	0.81	0.84	0.03
	[0.01]	[0.01]	[0.02]	[0.03]
HP par=100	0.78	0.79	0.76	-0.04
	[0.03]	[0.02]	[0.07]	[0.09]
HP par=6.25	0.81	0.81	0.81	0.01
	[0.01]	[0.02]	[0.03]	[0.04]
corr(TFP, H)				
First Diff.	-0.10	0.00	-0.21	-0.21
	[0.05]	[0.05]	[0.05]	[0.09]
CF	-0.02	0.08	-0.11	-0.19
	[0.04]	[0.05]	[0.03]	[0.06]
HP par=100	-0.14	-0.03	-0.27	-0.24
	[0.06]	[0.07]	[0.05]	[0.10]
HP par=6.25	-0.06	0.05	-0.17	-0.22
	[0.05]	[0.06]	[0.03]	[0.08]
corr(LP, GDP)				
First Diff.	0.73	0.73	0.71	-0.02
	[0.02]	[0.02]	[0.03]	[0.04]
CF	0.72	0.71	0.74	0.02
	[0.02]	[0.02]	[0.03]	[0.04]
HP par=100	0.72	0.71	0.70	-0.01
	[0.03]	[0.03]	[0.07]	[0.08]
HP par=6.25	0.72	0.71	0.71	0.00
	[0.02]	[0.02]	[0.04]	[0.04]
corr(LP, H)				
First Diff.	-0.30	-0.22	-0.40	-0.18
	[0.04]	[0.05]	[0.04]	[0.08]
CF	-0.23	-0.13	-0.32	-0.19
	[0.04]	[0.05]	[0.03]	[0.07]
HP par=100	-0.32	-0.22	-0.42	-0.21
	[0.05]	[0.06]	[0.04]	[0.09]
HP par=6.25	-0.27	-0.16	-0.38	-0.21
	[0.05]	[0.06]	[0.03]	[0.07]

Table 1.13: [Table 1.3 with standard errors] Average industry-level cyclical correlations between selected productivity measures and output, resp. hours. Weighted averages using constant industry weights over time: average nominal output share between 1960 and 1983. Comparison pre- and post-1984. Standard errors computed using bootstrapping (re-sampling the series 800 times using 6 years blocks).

	1960-2005	1960-1983	1984-2005	Difference
corr(TFPm, GDP)				
First Diff.	0.76	0.77	0.73	-0.04
CF	0.78	0.77	0.78	0.00
HP par=100	0.75	0.75	0.71	-0.04
HP par=6.25	0.77	0.77	0.75	-0.01
corr(TFPm, H)				
First Diff.	-0.14	-0.03	-0.25	-0.22
CF	-0.08	0.02	-0.19	-0.21
HP par=100	-0.14	-0.04	-0.25	-0.21
HP par=6.25	-0.10	0.01	-0.21	-0.22
corr(LP, GDP)				
First Diff.	0.74	0.76	0.68	-0.08
CF	0.74	0.74	0.72	-0.02
HP par=100	0.73	0.74	0.67	-0.06
HP par=6.25	0.74	0.74	0.70	-0.04
corr(LP, H)				
First Diff.	-0.33	-0.23	-0.43	-0.20
CF	-0.29	-0.19	-0.39	-0.20
HP par=100	-0.32	-0.24	-0.41	-0.18
HP par=6.25	-0.30	-0.21	-0.40	-0.20

Table 1.14: Average industry-level cyclical correlations between selected productivity measures and output, resp. hours. Robustness: simple averages, unit industry weights. Comparison pre- and post-1984. Each correlation is computed using four different detrending methods.

1.C Bottom-up construction of aggregate series

1.C.1 Time-varying industry weights

Approximation formulas

Let us assume that the aggregate variable X_t can be expressed (exactly) as

$$X_t = \sum_{i=1}^{N} \hat{w}_{i,t} x_{i,t}, \tag{1.46}$$

where x_{it} are the industry level series and $\hat{w}_{it}$ are time varying weights. Then, for the growth rate of the aggregate variable it follows that

$$
\begin{aligned}
\tilde{X}_{t+1} &= \frac{X_{t+1}-X_t}{X_t} \\
&= \frac{1}{X_t}\left(\sum_{i=1}^{N}\hat{w}_{i,t+1}x_{i,t+1} - \sum_{i=1}^{N}\hat{w}_{i,t}x_{i,t}\right) \\
&= \frac{1}{X_t}\left(\sum_{i=1}^{N}\hat{w}_{i,t+1}x_{i,t+1} - \sum_{i=1}^{N}\hat{w}_{i,t}x_{i,t+1} + \sum_{i=1}^{N}\hat{w}_{i,t}x_{i,t+1} - \sum_{i=1}^{N}\hat{w}_{i,t}x_{i,t}\right) \\
&= \frac{1}{X_t}\left(\sum_{i=1}^{N}\hat{w}_{i,t}(x_{i,t+1}-x_{i,t}) + \sum_{i=1}^{N}(\hat{w}_{i,t+1}-\hat{w}_{i,t})x_{i,t+1}\right) \\
&= \frac{1}{X_t}\left(\sum_{i=1}^{N}\hat{w}_{i,t}x_{i,t}\tilde{x}_{i,t+1} + \sum_{i=1}^{N}\tilde{w}_{i,t+1}\hat{w}_{i,t}x_{i,t+1}\right) \\
&= \sum_{i=1}^{N}w_{i,t+1}\tilde{x}_{i,t+1} + \sum_{i=1}^{N}\tilde{w}_{i,t+1}\frac{\hat{w}_{i,t}x_{i,t+1}}{X_t},
\end{aligned}
$$

where $\tilde{x}_{i,t}$ is the growth rate between periods t and $t-1$ of industry-level variable x_i, $\tilde{w}_{i,t+1}$ is the growth rate of weight $\hat{w}_i$ and where in the last equation we have defined

$$w_{i,t+1} = \frac{\hat{w}_{i,t}x_{i,t}}{X_t}.$$

Notice that if the growth rate of weights $\tilde{w}_{i,t+1}$ is small, the second term is negligible and we obtain expression

$$\tilde{X}_t \approx \sum_{i=1}^{N} w_{i,t}\tilde{x}_{i,t}. \tag{1.47}$$

Weights

For gross output, value added, capital, hours and industry-level total intermediate inputs, the aggregate nominal value is the sum of industry nominal values. Thus, I can substitute into equation 1.46 directly with

$$X_t^{real} = \sum_{i=1}^{N}\frac{p_{i,t}^{x}}{P_t^{X}}x_{i,t}^{real}, \tag{1.48}$$

where x_i is the industry variable of interest, $p_{i,t}^x$ is the price of $x_{i,t}$ and P_t^X is the corresponding price index. It follows that I can substitute into 1.46 and 1.47

$$\hat{w}_{it} = \frac{p_{i,t}^{x}}{P_t^{X}}, \tag{1.49}$$

$$w_{i,t+1} = \frac{p_{i,t}^{x}x_{i,t}}{P_t^{X}X_t}. \tag{1.50}$$

Notice that $w_{i,t+1}$ is the nominal cost share of industry i at time t.

Variable	**Flex. weights** rel. std. dev.	**Constant weights** relative std. dev. sample mean	pre-1984 mean
Value added	1.00	0.97	1.04
Gross output	1.00	0.98	1.04
Measured TFP	1.00	0.91	0.98
Labor productivity	1.00	0.94	1.01
Hours	1.00	1.02	1.05
Capital	1.00	1.12	1.08
Inter. inputs	1.00	1.00	1.02

Table 1.15: Relative standard deviations of weighted averages compared to the original aggregate series. Weighted averages constructed using flexible time-varying weights and constant weights (sample mean and pre-1984 mean weights).

For labor productivity it is straightforward to derive that

$$LP_t = \frac{VA_t}{H_t} = \frac{\sum_{i=1}^{N} \frac{p_{i,t}^{VA}}{P_t^{VA}} va_{i,t}}{H_t} \tag{1.51}$$

$$= \sum_{i=1}^{N} \frac{p_{i,t}^{VA}}{P_t^{VA}} \frac{va_{i,t}}{h_{i,t}} \frac{h_{i,t}}{H_t} \tag{1.52}$$

$$= \sum_{i=1}^{N} \frac{p_{i,t}^{VA}}{P_t^{VA}} \frac{h_{i,t}}{H_t} lp_{i,t}. \tag{1.53}$$

Therefore, I can substitute in equations 1.46 and 1.47 with

$$\hat{w}_{i,t} = \frac{p_{i,t}^{VA}}{P_t^{VA}} \frac{h_{i,t}}{H_t} \tag{1.54}$$

$$w_{i,t+1} = \frac{p_{i,t}^{VA} va_{i,t}}{P_t^{VA} VA_t}. \tag{1.55}$$

For measured TFP, I follow Hulten (1978) and use Domar weights for aggregating gross-output based industry total factor productivity into value-added based aggregate series, which gives me

$$w_{i,t+1} = \frac{p_{i,t} y_{i,t}}{P_t^{VA} VA_t}, \tag{1.56}$$

where y_i stands for industry gross output and VA stands for aggregate value added.

Quality of approximation

To assess the quality of approximation of the aggregate series by the bottom-up formulas I plot the comparison of different versions of the aggregate series in figure 1.7. The quality of approximation by the formula with time-varying weights is very good. Table 1.15 reports the relative standard deviation of weighted average series compared to the original aggregate series. The relative standard deviation is very close to one for each of the series.

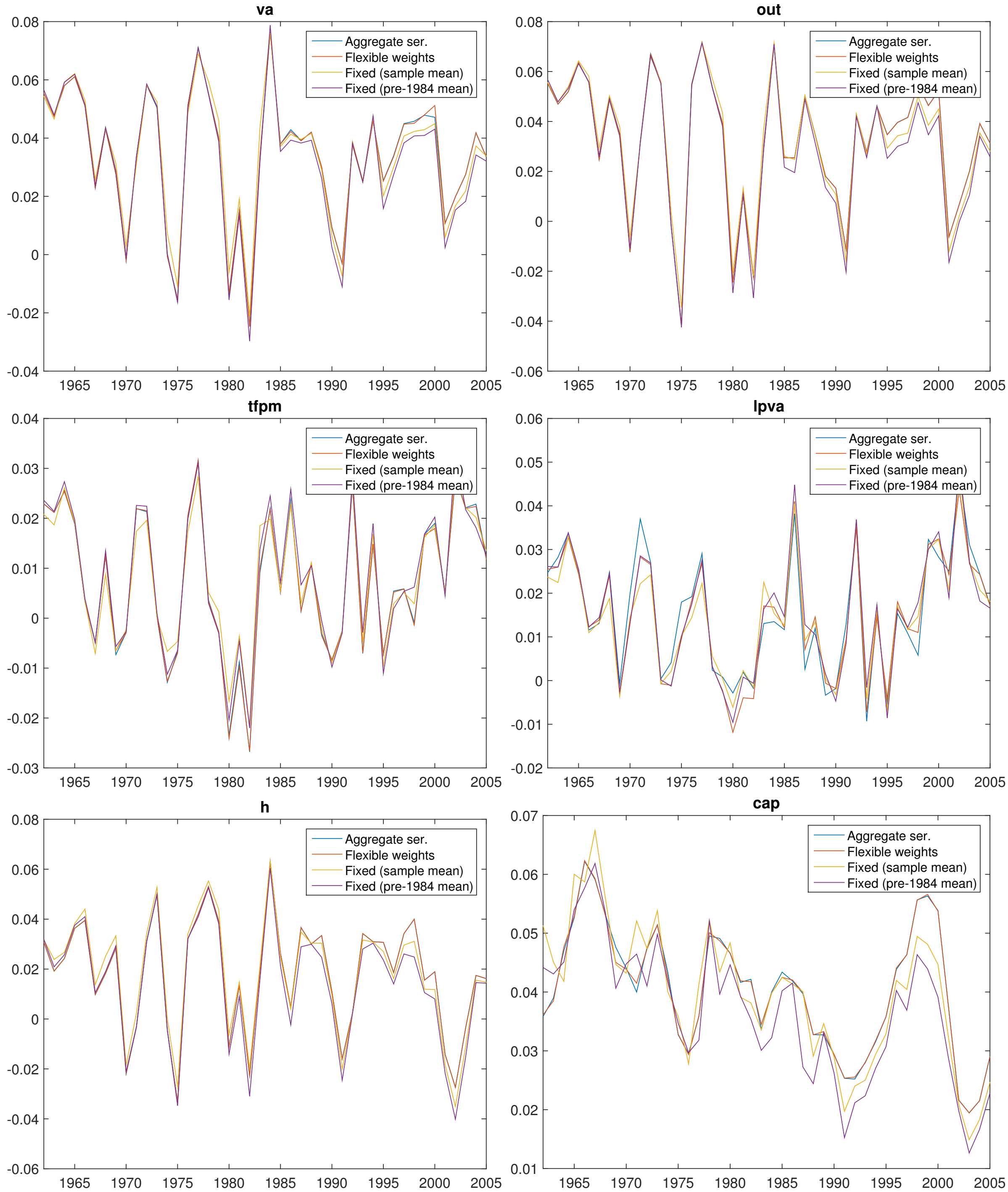

Figure 1.7: Comparison between aggregate series and weighted averages: value added (VA), gross output (OUT), measured TFP ($TFPm$), labor productivity (LP), hours (H) and capital (CAP). *Flexible weights* denote the series constructed using time-varying industry weights. *Fixed* series are plotted for two alternative weighing options - based on the whole sample and pre-1984 mean weights.

	1960-2005	1960-1983	1984-2005	Difference
corr(TFPm, GDP)				
First Diff.	0.70	0.83	0.51	-0.32
CF	0.82	0.81	0.65	-0.16
HP par=100	0.68	0.81	0.35	-0.45
HP par=6.25	0.75	0.79	0.47	-0.32
corr(TFPm, H)				
First Diff.	0.22	0.53	-0.19	-0.72
CF	0.47	0.52	0.04	-0.48
HP par=100	0.21	0.54	-0.28	-0.82
HP par=6.25	0.36	0.49	-0.15	-0.64
corr(LP, GDP)				
First Diff.	0.43	0.60	0.27	-0.33
CF	0.54	0.59	0.25	-0.33
HP par=100	0.49	0.60	0.28	-0.32
HP par=6.25	0.46	0.55	0.14	-0.41
corr(LP, H)				
First Diff.	-0.13	0.22	-0.46	-0.67
CF	0.09	0.22	-0.41	-0.63
HP par=100	-0.05	0.27	-0.40	-0.67
HP par=6.25	-0.02	0.18	-0.50	-0.68

Table 1.16: Fixed industry composition over time: Cyclical correlation between selected productivity measures and output/hours. Aggregate series using constant industry weights (mean over 1960-1983).

1.C.2 Constant weights

The constant-weight or fixed-weight aggregate series are weighted averages defined as

$$\tilde{X}_t \approx \sum_{i=1}^{N} \bar{w}_i \tilde{x}_{i,t}, \tag{1.57}$$

where constant weights $\bar{w}_i$ are averages over weights $w_{i,t}$ defined in the previous section. The benchmark weights are average shares over the pre-1984 period. The results are very robust with respect to different choice od weights.

Figure 1.7 plots the comparison of fixed-weight series to the original aggregate series. The fixed-weight series are still a very good approximation, although some differences are visible especially for capital. Second and third column of table 1.15 report the relative standard deviation of the fix-weight aggregate series compared to the aggregate series. For all variables with the exception of capital, the relative volatility is closer than 5% away from the aggregate series.

Table 1.16 reports the correlation between selected variables computed using the fixed-weight aggregate series for all detrending methods.

1.D Robustness exercises

In each of the robustness exercises, parameter ϵ and the volatilities of all types of shocks are recalibrated such that the targets listed in section 1.4.1 are matched.

1.D.1 Elasticity of substitution $\sigma = 0.5$

Aggregate	correlation productivity with output	with hours	rel. std.dev. hours	std.dev. output
Data				
Pre-1984	0.83	0.53	0.89	0.028
Post-1984	0.51	-0.19	1.20	0.018
Model				
Benchmark calibration	0.67	0.53	0.88	0.028
Flexible hours	-0.05	-0.19	1.02	0.032
Smaller dem. shocks	0.59	0.34	0.86	0.017

Table 1.17: Selected aggregate second moments, alternative value of the elasticity of substitution $\sigma = 0.5$. Data (top panel) and model simulations (bottom panel).

Industry	correlation productivity with output	with hours	rel. std.dev. hours	std.dev. output
Data				
Pre-1984	0.81	0.00	0.63	0.080
Post-1984	0.79	-0.21	0.57	0.076
Model				
Benchmark calibration	0.54	0.25	0.87	0.083
Flexible hours	0.12	-0.17	1.01	0.091
Smaller dem. shocks	0.54	0.24	0.87	0.080

Table 1.18: Selected averages of industry-level second moments, alternative value of the elasticity of substitution $\sigma = 0.5$. Data (top panel) and model simulations (bottom panel).

1.D.2 Elasticity $\rho = 0.5$

Aggregate	correlation productivity with output	with hours	rel. std.dev. hours	std.dev. output
Data				
Pre-1984	0.83	0.53	0.89	0.028
Post-1984	0.51	-0.19	1.20	0.018
Model				
Benchmark calibration	0.66	0.53	0.89	0.028
Flexible hours	-0.06	-0.19	1.02	0.032
Smaller dem. shocks	0.59	0.39	0.88	0.018

Table 1.19: Selected aggregate second moments, alternative value of the intertemporal elasticity $\rho = 0.5$. Data (top panel) and model simulations (bottom panel).

Industry	correlation productivity with output	with hours	rel. std.dev. hours	std.dev. output
Data				
Pre-1984	0.81	0.00	0.63	0.080
Post-1984	0.79	-0.21	0.57	0.076
Model				
Benchmark calibration	0.56	0.27	0.86	0.076
Flexible hours	0.18	-0.11	0.99	0.085
Smaller dem. shocks	0.56	0.26	0.86	0.073

Table 1.20: Selected averages of industry-level second moments, alternative value of the intertemporal elasticity of substitution $\rho = 0.5$. Data (top panel) and model simulations (bottom panel).

1.D.3 Frisch elasticity of labor supply $\eta^{Frisch} = 1$

Aggregate	correlation productivity with output	with hours	rel. std.dev. hours	std.dev. output
Data				
Pre-1984	0.83	0.53	0.89	0.028
Post-1984	0.51	-0.19	1.20	0.018
Model				
Benchmark calibration	0.65	0.53	0.89	0.028
Flexible hours	-0.05	-0.19	1.02	0.030
Smaller dem. shocks	0.59	0.39	0.88	0.019

Table 1.21: Selected aggregate second moments, alternative value of the Frisch elasticity of labor supply $\eta^{Frisch} = 1$. Data (top panel) and model simulations (bottom panel).

Industry	correlation productivity with output	with hours	rel. std.dev. hours	std.dev. output
Data				
Pre-1984	0.81	0.00	0.63	0.080
Post-1984	0.79	-0.21	0.57	0.076
Model				
Benchmark calibration	0.56	0.29	0.86	0.081
Flexible hours	0.17	-0.11	0.99	0.087
Smaller dem. shocks	0.56	0.28	0.86	0.078

Table 1.22: Selected averages of industry-level second moments, alternative value of the Frisch elasticity of labor supply $\eta^{Frisch} = 1$. Data (top panel) and model simulations (bottom panel).

1.E Additional analytical results

1.E.1 Analytical derivation of corr(Y,LP)

At the industry level, the correlation between measured productivity and output can be expressed as (for the elasticity of substitution σ equals one):

$$\mathrm{Corr}(\tilde{lp_i}, \tilde{y}_i) = \frac{\frac{\mathrm{Var}(\tilde{z}_i)}{\mathrm{Var}(\tilde{h}_i)} + \Gamma B}{\sqrt{\frac{\mathrm{Var}(\tilde{z}_i)}{\mathrm{Var}(\tilde{h}_i)} + \Gamma^2}\sqrt{\frac{\mathrm{Var}(\tilde{z}_i)}{\mathrm{Var}(\tilde{h}_i)} + B^2}}. \tag{1.58}$$

Equation 1.58 expresses the correlation in terms of two factors: the parameter Γ (resp. $B = \Gamma + 1$) and the relative variance of industry technology $\tilde{z}_i$ and hours $\tilde{h}_i$.

For the aggregate variables, it follows that (for the case when the elasticity ρ equals one):

$$\mathrm{Corr}(\tilde{LP}, \tilde{Y}) = \frac{\frac{\mathrm{Var}(\tilde{Z})}{\mathrm{Var}(\tilde{H})} + \Gamma B}{\sqrt{\frac{\mathrm{Var}(\tilde{Z})}{\mathrm{Var}(\tilde{H})} + \Gamma^2}\sqrt{\frac{\mathrm{Var}(\tilde{Z})}{\mathrm{Var}(\tilde{H})} + B^2}}. \tag{1.59}$$

In equations 1.58 and 1.59, the exogenous shocks only influence the variance ratios. The corner case in which the variance ratio approaches infinity implies unit correlation. Coefficient Γ determines the sign of the correlation. For positive values of Γ, also the other corner case in which the variance ratio is equal to zero implies unit correlation. Between the two corner cases, the correlation decreases but can not switch signs. In fact, it can be shown that the correlation is higher or equal to a positive constant $c^{\Gamma} = \frac{2\sqrt{B\Gamma}}{B+\Gamma}$ for any positive value of the variance ratio.

The comparison of equations 1.58 and 1.59 delivers the key insights analogous to section 1.5.

1.E.2 Frisch elasticity of labor supply

As there are different margins of labor input in my model, I also have several differing concepts of the labor supply elasticity. In what follows, I derive a measure that corresponds to the standardly used Frisch elasticity of labor supply.

Using the functional form 1.15, equation 1.25 can be reformulated as

$$D w_i C^{-\rho} = \Theta {h_i}^{\frac{\epsilon\eta}{1+\epsilon}}, \tag{1.60}$$

where Θ is a constant. Thus, at the industry level, Frisch elasticity can be expressed as

$$EL^{Frisch} = \frac{1}{\eta^{Frisch}} = \frac{1+\epsilon}{\epsilon\eta} = \frac{1}{\eta}\left(1 + \frac{1}{\epsilon}\right) > \frac{1}{\eta} \tag{1.61}$$

Since the elasticity is the same in all industries, it also apply to the aggregate labor supply.

2 Technology, demand, and productivity: what an industry model tells us about business cycles

This chapter is joint work with Michael Reiter.

2.1 Introduction

What type of shocks are driving business cycles? Contemporary workhorse DSGE models often feature a wide variety of shocks, the importance of which might vary over time. For many of the commonly used types of these shocks, there are prevailing controversies about whether they can be interpreted as structural sources of the fluctuations, see for example Chari et al. (2009). In contrast, many models in the theoretical literature are still built on the assumption that business cycles are driven solely by technology shocks.

However, the plausibility of aggregate technology shocks, i.e., changes in factor productivity affecting the whole economy, has long been disputed in the macroeconomic literature, see e.g. Summers (1986). These shocks are not directly observed, and are hard to identify. Identification of technology shocks with the use of Solow residuals, for example, suffers from issues regarding the measurement of inputs and outputs, such as composition effects and variable capacity utilization.[1]

Technological changes at the level of narrowly defined industries appear more plausible and probably easier to identify because their fluctuations are larger and therefore less likely to be dominated by mismeasurement. Thus, a branch of literature has emerged that studies whether independent shocks at various levels of disaggregation can explain the aggregate fluctuations. Focusing mostly on the mechanisms that propagate idiosyncratic shocks across the economy within the RBC framework, the conclusion so far is that only a part of the fluctuations in aggregate productivity can be accounted to the independent industry-level shocks, see our summary in section 2.1.1 for more detail.

In this paper, we study the role of the different types of shocks in generating business cycle fluctuations in a New Keynesian DSGE model, building on the growing literature on multi-industry business cycle models. We calibrate the model to industry-level U.S. data. Our model has the following key characteristics. First, the production of goods is highly disaggregated, composed of 77 industries connected through the input-output network. Second, the economy is driven by technology and demand-side shocks at both the aggregate and the industry level. Third, endogenous factor utilization allows non-technology shocks to generate changes in measured

[1] Further, identification approaches based on structural VAR models rely heavily on the identifying assumptions, see e.g. Erceg et al. (2005).

productivity. Fourth, there are nominal rigidities at the firm level, in line with the New Keynesian literature. The nominal rigidities are important because the price mechanism is central for the propagation of shocks via the input-output network. For example, an increase in industry productivity only leads to higher industry output if the prices reflect the change in productivity. While the model features a detailed industry structure, it only includes four types of shocks, less than a typical medium-sized DSGE model. At the aggregate level, our model features one demand side shock and one productivity shock. Additionally, each industry is affected by its own idiosyncratic shock to demand and productivity. We show that this parsimonious shock structure delivers a very good fit of the model along many dimensions at the aggregate and industry level.

We find that although the exogenous shocks to technology are necessary for our model to fit the data, these shocks are exclusively industry-specific. The variance of the aggregate technology shock is zero. The remaining three types of shocks generate the observed fluctuations of aggregate and industry variables, as well as the co-movement pattern across industry-level variables. The majority of the aggregate fluctuations, including those in aggregate measured productivity, are explained through the shocks to aggregate demand. On the other hand, industry-specific technology and demand shocks are the dominant drivers of fluctuations at the industry level. Industry-specific shocks to technology are necessary to explain the strong fluctuations of measured productivity at the industry level. Moreover, they also contribute a significant part to the volatility of measured productivity at the aggregate level.

Our model can generate the observed fluctuations in aggregate productivity without aggregate technology shocks as a result of the combination of two elements. First, the contribution of industry-level shocks to aggregate productivity, and second, endogenous fluctuations arising from variable factor utilization (effort) and increasing returns to scale (fixed costs). These mechanisms allow non-technology shocks to contribute to fluctuations in measured productivity.

Our results are compatible with recent evidence that the bulk of aggregate macroeconomic fluctuations is driven by one type of shock that has the characteristics of a demand shock, see Angeletos et al. (2020), Andrle et al. (2017). We support these findings by using industry-level evidence, which brings in a host of information that is useful for the identification of shocks. We find that, considering aggregate data only, it is difficult to distinguish a model with aggregate technology shocks from a model that relies on endogenous productivity fluctuations. However, we show that these models have quite different implications for the industry-level variables. One important piece of industry-level evidence is the co-movement of the variables, especially measured productivity, across industries. Moreover, the models differ in their implications for the size of fluctuations of industry variables relative to aggregate variables and for the cyclicality of productivity.

Our second finding is that about a half of the decrease in the cyclicality of measured productivity in the U.S. in the period after 1984 can be explained by the reduction in the size of demand shocks, in line with the narrative of the *great moderation*. We refer to the empirical observations that the procyclicality of measured productivity in the U.S. has to a large extent disappeared in the period after 1984, see Stiroh (2009) and Galí and Gambetti (2009). Several authors, for example Galí and Gambetti (2009) and Barnichon (2010), have suggested that the great moderation period after

1984 was characterised by a different composition of shocks, especially stressing the lower volatility of shocks to aggregate demand, or muted effects of these shocks on the economy. Thus, we assume a lower volatility of the shocks to aggregate demand for the period after 1984, keeping the rest of parameters the same. The correlation between aggregate measured TFP and hours decreases from 0.49 to 0.11, corresponding to 50% of the change observed in the data. Importantly, our model is able to generate the decrease in the procyclicality of the aggregate measured productivity without generating counterfactual changes at the industry level.

The rest of the paper is structured as follows. After discussing the existing literature in section 2.1.1, we introduce the multi-industry New Keynesian general equilibrium model in section 2.2. We describe the data sources and the calibration strategy in section 2.3. Section 2.4 presents and discusses the results. Finally, section 2.5 concludes.

2.1.1 Relationship to the existing literature

Productivity shocks have played a prominent role in macroeconomics over the last four decades. They were the only shocks driving the economic fluctuations in the early RBC models, starting with Kydland and Prescott (1982) and Long and Plosser (1983). In the contemporary medium-sized DSGE models, as they are routinely used in central banks, technology shocks are as a rule included in the set of structural shocks that drive the business cycles. At the same time, these shocks continue to play an important role in the academic literature, e.g. macroeconomic models with financial frictions starting from Kiyotaki and Moore (1997); the literature investigating whether the fluctuations in the unemployment can be explained by the aggregate shocks to productivity (Shimer 2005, Costain and Reiter 2008, Hagedorn and Manovskii 2008, Hall and Milgrom 2008). At the same time, these shocks have been subject to ongoing critique, see for example Francis and Ramey (2005), Chari et al. (2009).

The idea that industry-specific technology shocks might add up to sizeable technology shocks in the aggregate goes back at least to Long and Plosser (1983) and has attracted renewed attention in recent years. The law of large numbers suggests that idiosyncratic shocks at firm or industry level quickly wash out and cannot drive the aggregate fluctuations. However, Horvath (1998), Horvath (2000), Dupor (1999), Acemoglu et al. (2012), and Acemoglu et al. (2017) point out that idiosyncratic shocks might propagate between industries due to input-output linkages and thus affect the aggregate fluctuations more strongly than the law of large numbers would predict. The focus of the papers lies on the properties of the input-output network that amplify the transmission of shocks across industries. They show that network asymmetry with respect to the number of downstream industries is crucial for the ability of the models to generate substantial aggregate fluctuations from industry-specific shocks. Other channels of amplification of the macroeconomic impact of microeconomic shocks are studied in Baqaee (2018) and Baqaee and Farhi (2019). Gabaix (2011) and Carvalho and Gabaix (2013) stress the importance of large firms and the fat-tailed distribution of firm size in generating the aggregate fluctuations.

Following the idea of industry-level shocks propagated through the input-output network, Foerster et al. (2011), Holly and Petrella (2012), Atalay (2017) and vom Lehn and Winberry (2020) use various approaches to quantify the relative importance of both industry-specific and aggregate shocks for the macroeconomic fluctuations. Foerster et al. (2011) use factor analysis to decompose the industrial production series into the aggregate and idiosyncratic components and adjust the results for the contribution of the input-output network. They estimate that industry-specific shocks are responsible for 20% to 50% of the aggregate fluctuations, depending on the sample period (industry specific shocks are more important in the period after the mid-1980s). However, their RBC model only features technology shocks. Holly and Petrella (2012) utilize an industry-level VAR model of the U.S. manufacturing and identify the industry-specific shocks to productivity using the long-run restrictions proposed by Galí (1999) at the industry level. Their estimates are broadly in line with the results of our paper for both aggregate and industry-level fluctuations. They find a very limited role of aggregate shocks to technology, while industry-level shocks to technology play an important role. The industry-specific shocks in Holly and Petrella in general explain a somewhat bigger part of the fluctuations of aggregate variables than in our paper, which can be attributed to a different concept of the industry-specific shock to demand.

Atalay (2017) and vom Lehn and Winberry (2020) are closely related to the present paper, although both feature RBC models with supply side shocks only. Atalay estimates a structural industry-level model with a generalized production function. He shows that the elasticities of substitution between production factors, between intermediate inputs from different industries and between the consumption of industry-level goods are important determinants of how strongly shocks propagate between industries. He identifies low elasticities which suggest complementarity between industry goods and imply that industry-specific shocks account for roughly a half of the fluctuations of the aggregate output.

Vom Lehn and Winberry (2020) is the only paper which also examines the vanishing cyclicality of productivity in the U.S. in the mid-1980s using the industry approach. They find that the industries which act as suppliers of the investment goods are important drivers of the aggregate fluctuations and that idiosyncratic shocks to these industries generate countercyclical movement in aggregate measured productivity. Since the relative importance of the shocks to these industries has increased in the recent decades, their model generates the decrease in the cyclicality of productivity. Such explanation is complementary to ours as their model completely abstracts from the demand-side shocks. The vanishing cyclicality of productivity in vom Lehn and Winberry relies on assumption of the decreasing returns to scale, which is not present in our model.

The main point in which we deviate from the existing literature is our focus on the identification of demand versus supply side shocks. We construct a New Keynesian model and include shocks with characteristics typical for each side. We indeed find that our aggregate demand shocks are the key driver of the aggregate fluctuations. Second, we allow for endogenous factor utilization formalized as workers' effort, which is not observable by the econometrician. The approach is based on the empirical work of Basu et al. (2006), who estimate the contribution of factor utilization and true technology shocks for the U.S. industries. The factor utilization channel is important, because it allows the model to generate variation in the measured productivity without exogenous shocks to technology. Several of the models in the literature (Foerster et al. 2011, Atalay 2017, etc.) conclude that the aggregate technology shocks are important drivers of business cycle fluctuations because such shocks are basically the only shocks able to generate substantial co-movement in the measured productivity across industries. Hence, throughout this paper, we rigorously distinguish between exogenous shocks to *technology* and observable *measured productivity.*

The substantial decrease in the cyclicality of measured productivity in the U.S. in the mid-1980s has been documented by a number of papers starting from Stiroh (2009), Galí and Gambetti (2009) with further important empirical insights in Fernald and Wang (2016). The studies have documented a robust decline in the correlations between measured aggregate productivity and aggregate output, resp. production inputs across the two time periods: first, the post-war period between 1950 and the mid-1980s which we refer to as *pre-1984* period and second, the *post-1984* period from 1984 up to 2015, where the end date depends on data availability. Various explanations have been proposed by the rich theoretical and empirical literature, including Barnichon (2010), Galí and van Rens (2020), Lewis et al. (2019), Evans (2019), Berger (2018), Riggi (2019), Garin et al. (2018) and others, see Molnárová (2020) for a discussion of the existing explanations.

Molnárová (2020) also points out the importance of industry-level evidence for discriminating between the various mechanisms that try to explain the vanishing cyclicality of productivity, since the change in the cyclicality is virtually non-existent at the level of individual industries. However, the existing explanations have qualitatively different implications for the industry-level moments. In this paper we focus on a mechanism that is able to generate a decrease in the procyclicality of measured productivity without generating counterfactual predictions at the industry level, which is the change in the structure of shocks, see Barnichon (2010), Foerster et al. (2011), Galí and Gambetti (2009). We find that our model generates a significant part of the decrease in the procyclicality of measured productivity observed in the U.S. when we change the composition of the shocks in line with the literature estimates for the post-1984 period.

Lastly, this paper is also related to the recent strand of literature that studies the propagation of shocks in industry-level New Keynesian models. The models in this literature are closely related to ours, but the papers have a different focus, concentrating mostly on the heterogeneity of industry-level inflation and transmission of monetary policy shocks. Bouakez et al. (2014), Pasten et al. (2017) and Pasten et al. (2018) point out the importance of heterogeneous price rigidity across industries, amplified through the input-output linkages. Bouakez et al. focus on a narrow selection of shocks, excluding the shock to aggregate technology and industry-specific demand shocks. They show that the heterogeneous response of prices across industries are per se very important for the transmission of the effects of the monetary policy. Smets et al. (2019) estimate a New Keynesian model using Bayesian techniques and find that the input-output linkages are the major source of heterogeneous inflation patterns across industries and that industry-level shocks contribute to aggregate inflation volatility.

2.2 Model

This section presents the New Keynesian DSGE model with production disaggregated at the industry level, featuring 77 industries which are linked via the input-output network. The model economy is subject to two types of aggregate shocks, one technology shock and one shock to aggregate demand. In addition, each industry is subject to idiosyncratic shocks to its technology and demand. The input-output network propagates the industry-specific shocks through the economy. We use the model to study the role of demand and supply side shocks in the fluctuations of industry-level and aggregate variables, with particular focus on measured productivity. Therefore, the model incorporates an endogenous factor utilization margin which creates a wedge between *measured total factor productivity* and exogenous *technological* improvements.

Because we model each industry individually, the model features a very large number of variables. We solve the model by linearization around the deterministic steady state.

2.2.1 Industries

Production in the model economy is organized into I different industries, indexed by $i = 1, \dots, I$. The output of each industry has three potential purposes. It is used as a *consumption good* (cf. section 2.2.2), in the production of *investment goods* (section 2.2.4), or as an *intermediate input* in the production of firm output (section 2.2.3).

Each industry consists of a continuum of monopolistically competitive firms represented by the unit interval. The differentiated firm goods aggregate to industry output according to

$$y_{i,t} = \left(\int_0^1 y_{ki,t}{}^{\frac{\sigma_I - 1}{\sigma_I}} dk \right)^{\frac{\sigma_I}{\sigma_I - 1}}, \tag{2.1}$$

where $y_{ki,t}$ denotes the output produced by an individual firm k in industry i and $\sigma_I > 0$ is the elasticity of substitution between the firm goods. The aggregator 2.1 implies iso-elastic demand for goods of firm k:

$$y_{ki,t} = \left(\frac{p_{ki,t}}{p_{i,t}} \right)^{-\sigma_I} y_{i,t}. \tag{2.2}$$

Here $p_{ki,t}$ is the price set by firm k, and $p_{i,t}$ is the price index of industry i, given by

$$p_{i,t} = \left(\int_0^1 p_{ki,t}{}^{1-\sigma_I} dk \right)^{\frac{1}{\sigma_I - 1}}. \tag{2.3}$$

2.2.2 Households

The economy is populated by a continuum of infinitely-lived representative households. Households provide labor input, consume goods, save in the form of bonds and capital, and receive all firm profits. The objective of the representative household is to maximize

$$\mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\ln(C_t - \chi \bar{C}_t) - \frac{N_t{}^{1+1/\sigma_U}}{1 + 1/\sigma_U} \right], \tag{2.4}$$

where C_t are units of a bundle of consumed goods and the term $\chi \bar{C}_t$ represents consumption habits that are assumed to be external to the individual household, $\bar{C}_t = C_{t-1}$. N_t is an index of the labor services provided to various industries and σ_U is the corresponding elasticity of the total labor supply.

The consumption bundle is a composite of differentiated industry goods

$$C_t = \left(\sum_{i=1}^{I} {v_{i,t}}^{\frac{1}{\sigma_C}} {c_{i,t}}^{\frac{\sigma_C - 1}{\sigma_C}} \right)^{\frac{\sigma_C}{\sigma_C - 1}} \tag{2.5}$$

where $c_{i,t}$ is the amount of industry i good that is used for consumption, $v_{i,t}$ is the weight of that good in the consumption basket and $\sigma_C > 0$ is the elasticity of substitution between the industry goods. The weights are subject to exogenous variation over time, which we interpret as *shocks to relative industry demand*, specified in more detail in section 2.2.7. We normalize the shocks to relative demand such that their effect on the aggregate price level is neutralized up to a first order approximation.

The price P_t of a unit of the consumption bundle is defined so as to satisfy

$$P_t C_t = \sum_i p_{i,t}^{NOM} c_{i,t}, \tag{2.6}$$

where $p_{i,t}^{NOM}$ is the nominal price of industry good i. Expressing industry-prices relative to the price of consumption bundle, $p_{i,t} = p_{i,t}^{NOM}/P_t$, the iso-elastic demand function for goods of industry i is given as

$$c_{i,t} = {v_{i,t}}^{\sigma_C} {p_{i,t}}^{-\sigma_C} C_t. \tag{2.7}$$

Equations 2.6 and 2.7 imply that the relative prices satisfy

$$1 = \left(\sum_{i=1}^{I} v_{i,t} {p_{i,t}}^{1-\sigma_C} \right)^{\frac{1}{1-\sigma_C}}. \tag{2.8}$$

The utility function 2.4 states that households draw negative utility from providing an index N_t of labor services to various industries. The labor supply index is given by

$$N_t = \left(\sum_{i=1}^{I} \eta_i g(h_{i,t}, e_{i,t})^{\frac{\sigma_N + 1}{\sigma_N}} \right)^{\frac{\sigma_N}{\sigma_N + 1}}. \tag{2.9}$$

The disutility depends on the number of differentiated hours $h_{i,t}$, as well as the effort $e_{i,t}$ exerted by the workers in each industry. Workers' effort is a measure of performance that we assume is observed and remunerated by firms, but not observed in the data.

Similar to Horvath (2000) and Bouakez et al. (2014), household preferences over working in different industries are given by the weight parameters η_i and the elasticity parameter $\sigma_N > 0$. The latter determines how elastically the industry labor supply allocation reacts to changes in industry wages. For σ_N approaching infinity, labor inputs in various industries are perfect substitutes as far as the household is concerned. For $\sigma_N < \infty$, households prefer to diversify their labor input, thus the labor input is not perfectly mobile across industries. This specification allows for industry-specific wages in our representative household framework.

Finally, the function g describes household preferences over hours and effort. Utility is decreasing in both hours and effort supplied to each industry according to

$$g(h_{i,t}, e_{i,t}) = \left(\frac{h_{i,t}{}^{\sigma_h}}{\sigma_h} + \Lambda_i \frac{e_{i,t}{}^{\sigma_e}}{\sigma_e} \right)^{\frac{\sigma_h+\sigma_e}{\sigma_h\sigma_e}}, \tag{2.10}$$

where the parameters $\sigma_h \geq 0$ and $\sigma_e \geq 0$ determine the elasticity with which households adjust the supply of hours and effort, respectively, and $\Lambda_i \geq 0$ is an industry-specific parameter. Notice that g is jointly convex in hours and effort.

The total labor service available to the firms in industry i is the product of hours and effort,

$$l_{i,t} = e_{i,t} h_{i,t}. \tag{2.11}$$

Firms pay the wage $w_{i,t}$ per unit of labor service $l_{i,t}$ and the household can choose hours and effort optimally, such that the disutility of providing labor services $l_{i,t}$ is minimized, cf. Barnichon (2010). Household first order conditions imply

$$e_{i,t} = \Lambda_i{}^{-\frac{1}{\sigma_e}} h_{i,t}{}^{\frac{\sigma_h}{\sigma_e}}. \tag{2.12}$$

Hence, there is a monotonous relationship between hours and effort. Models with endogenous factor utilization often imply that it is optimal to adjust various input margins simultaneously, see Basu et al. (2006). This property of the model is useful, because in the data hours are observed but effort is not. The elasticity of effort response relative to that of hours only depends on the ratio of the parameters σ_h/σ_e. Without loss of generality, we normalize σ_h to one in all quantitative exercises. The higher the value of parameter σ_e, the less effort fluctuates in comparison to hours. Moreover, notice that as an immediate implication of equation 2.12, the function g is linear in labor input l_i.

With all prices expressed in terms of the consumption bundle, the budget constraint of the household is given by

$$\left(\sum_{i=1}^{I} w_{i,t} l_{i,t} \right) + r_t^k K_{t-1} + T_t + B_{t-1} r_t^b = C_t + P_t^X X_t + B_t, \tag{2.13}$$

where $w_{i,t}$ are real industry-specific wages per unit of labor input, K_t is capital stock at the end of period t, r_t^k is gross real return on capital, T_t are aggregate firm profits, X_t is gross investment and P_t^X is the real price of investment good.

Besides physical capital, the household can also save in the form of a one-period riskless bond, B_t. The bond yields the real return

$$r_t^b = D_{t-1} \frac{R_{t-1}}{\pi_t}, \tag{2.14}$$

where the nominal interest rate R_t is set by the monetary authority, and π_t is consumer price inflation. We interpret the exogenous disturbance term D_t as the aggregate demand shock. The shock represents a wedge between the nominal interest rate set by the monetary authority and the interest rate available to the household. This type of demand shock is used in the recent DSGE literature, for example Smets and Wouters (2007), where it is referred to as the *risk premium shock*.

2.2.3 Firms

In each industry, firms act under monopolistic competition and produce goods using capital and labor services as well as intermediate inputs. Firms maximize the expected discounted value of their future profits.

All firms in an industry have access to the same technology and are the same ex ante. Therefore, in order to simplify the formulas, we omit firm indices in the following firm-level equations. The gross output of a firm in industry i follows

$$y_{i,t} = A_t z_{i,t} \left[\mu_{i,K}{}^{\frac{1}{\sigma_y}} k_{i,t}{}^{\frac{\sigma_y - 1}{\sigma_y}} + \mu_{i,L}{}^{\frac{1}{\sigma_y}} l_{i,t}{}^{\frac{\sigma_y - 1}{\sigma_y}} + \mu_{i,M}{}^{\frac{1}{\sigma_y}} M_{i,t}{}^{\frac{\sigma_y - 1}{\sigma_y}} \right]^{\frac{\sigma_y}{\sigma_y - 1}} - \Phi_i, \tag{2.15}$$

where A_t is exogenous stochastic aggregate technology that affects all the industries. In contrast, $z_{i,t}$ is a technology process that only affects firms in industry i. The production factors capital $k_{i,t}$, labor $l_{i,t}$, and intermediate inputs $M_{i,t}$ are combined with elasticity of substitution $\sigma_y > 0$. The weights $\mu_{i,\times}$ determine the relative importance of the production factors. The intermediate input composite $M_{i,t}$ is produced from industry goods with a constant returns to scale technology

$$M_{i,t} = \left(\sum_{j=1}^{I} \alpha_{ji}{}^{\frac{1}{\sigma_M}} m_{ji,t}{}^{\frac{\sigma_M - 1}{\sigma_M}} \right)^{\frac{\sigma_M}{\sigma_M - 1}},$$

where $m_{ji,t}$ denotes the intermediate good from industry j that a firm in industry i uses to produce its output. The parameter $\sigma_M > 0$ is the elasticity of substitution between intermediate inputs from different industries. The weights $\alpha_{ji} \geq 0$ determine the relative importance of intermediate inputs from various industries.

In order to produce, firms in industry i must pay a fixed cost $\Phi_i \geq 0$. Because of the fixed cost, the firms face increasing returns to scale in net output and changes in demand generate changes in measured productivity. Next to endogenous factor utilization, fixed costs are another reason why changes in measured productivity are different from exogenous technological changes.

The firms are subject to nominal price rigidities of the Calvo-type. Since the firms in industry i are ex ante identical, they all choose the same optimal price $p^*_{i,t}$ conditional on adjusting. Substituting into 2.3, the price index of the good of industry i evolves according to

$$p_{i,t} = \left[\theta_i \left(\frac{p_{i,t-1}}{\pi_t} \right)^{1-\sigma_I} + (1 - \theta_i) p^*_{i,t}{}^{1-\sigma_I} \right]^{\frac{1}{1-\sigma_I}}, \tag{2.16}$$

where $\theta_i \in [0, 1]$ is the probability that a firm is not allowed to adjust the price in period t. As discussed amongst others in Bouakez et al. (2014), the degree of price stickiness is likely to differ across industries. However, the identification of the parameter θ at the industry level is difficult. Therefore, we use the same degree of price stickiness across all industries in the benchmark calibration, and check for robustness using the parameters θ_i identified by Bouakez et al. (2014).

The problem of a representative firm at time t is to choose the amount of capital, labor, intermediate inputs, and price of its good (if possible) in order to maximize the value of expected future profits. In nominal terms, the dynamic price-setting problem of the firms is to maximize

$$\mathrm{E}_t \sum_{s=0}^{\infty} {\theta_i}^s Q_{t,t+s} \left[y_{i,t+s|t} p_{i,t}^{NOM} - \mathcal{C}_{i,t+s|t} \right], \tag{2.17}$$

where $p_{i,t}^{NOM}$ is the nominal price set at time t and $y_{i,t+s|t}$ is period $t+s$ demand for goods of a firm in industry i that was last setting its prices in period t. $Q_{t,t+s}$ is nominal stochastic discount factor between periods t and $t+s$, defined as

$$Q_{t,t+s} = \beta^s \frac{\lambda_{t+s}}{\lambda_t} \frac{P_t}{P_{t+s}},$$

where λ_t denotes the marginal utility of consumption at period t. $\mathcal{C}_{i,t+s|t}$ are the firm nominal costs of producing output $y_{i,t+s|t}$. Apart from the fixed costs, the production is constant returns to scale. Thus, we can express the nominal costs in terms of the real marginal costs $RMC_{i,t}$ as

$$\mathcal{C}_{i,t+s|t} = P_{t+s} RMC_{i,t+s} (y_{i,t+s|t} + \Phi_i),$$

where the real marginal costs are given by

$$RMC_{i,t} = \frac{1}{A_t z_{i,t}} \left(\mu_{i,K} {r_t^k}^{1-\sigma_y} + \mu_{i,L} {w_{i,t}}^{1-\sigma_y} + \mu_{i,M} {P_{i,t}^M}^{1-\sigma_y} \right)^{\frac{1}{1-\sigma_y}}. \tag{2.18}$$

In the absence of nominal rigidities, profit maximization of the firms implies a price markup of $\frac{1}{\sigma_I - 1}$ over the marginal costs.

2.2.4 Investment and capital

Investment into physical capital uses the specialized investment good X. The amount of X_t produced is given by

$$X_t = \left(\sum_{i=1}^{I} {\xi_i}^{\frac{1}{\sigma_X}} {x_{i,t}}^{\frac{\sigma_X - 1}{\sigma_X}} \right)^{\frac{\sigma_X}{\sigma_X - 1}},$$

where $x_{i,t}$ is the amount of industry-i good that is used in the production of the investment good, ξ_i gives the weight of industry-i good in production, and the parameter $\sigma_X > 0$ is the elasticity of substitution between industry goods. The demand for the good of industry i is iso-elastic, given by

$$x_{i,t} = \xi_i \left(\frac{p_{i,t}}{P_t^X} \right)^{-\sigma_X} X_t. \tag{2.19}$$

The price of the investment good relative to consumption follows from the relative prices of the industry goods as

$$P_t^X = \left(\sum_{i=1}^{I} \xi_i {p_{i,t}}^{1-\sigma_X} \right)^{\frac{1}{1-\sigma_X}}. \tag{2.20}$$

Capital is subject to adjustment costs formulated as in Hayashi (1982). The costs are quadratic in investment intensity ι_t, defined as

$$X_t = \iota_t K_{t-1}. \tag{2.21}$$

The aggregate capital stock evolves according to

$$K_t = (1 - \delta)K_{t-1} + \phi(\iota_t)K_{t-1}. \tag{2.22}$$

Thus, for any investment intensity ι_t, the part $\phi(\iota_t)K_{t-1}$ that is added to the capital stock is given by

$$\phi(\iota_t) = \iota_t - \frac{(\iota_t - \delta)^2}{\kappa\delta},$$

where δ is rate of depreciation and κ is the parameter that determines the strength of the adjustment costs. This formulation of capital adjustment costs is equivalent to several other ways of introducing convex adjustment costs, cf. Wang and Wen (2010). While the aggregate capital stock in the model is rigid, there are no frictions to capital mobility across industries.

2.2.5 Monetary policy

Monetary policy follows a simple interest rate rule,

$$r_t = r^* + \gamma_r(r_{t-1} - r^*) + (1 - \gamma_r)\gamma_\pi(\pi_t - \pi^*). \tag{2.23}$$

Parameters r^* and π^* are the desired policy targets. Parameter $\gamma_r \geq 0$ determines the rigidity of the interest rate rule of the monetary authority. Parameter $\gamma_\pi > 1$ is the Taylor parameter that governs the strength with which the monetary authority reacts to the fluctuations of inflation.

2.2.6 Market clearing

All markets clear in equilibrium. In particular, for each industry good j, the total production equals the amount of good j used in the production of final good, investment good, and intermediate inputs to production in all industries

$$y_{j,t} = c_{j,t} + x_{j,t} + \sum_{i=1}^{I} m_{ji,t}. \tag{2.24}$$

2.2.7 Exogenous shocks

There are four types of exogenous structural shocks in our model. Two aggregate processes drive the aggregate technology A_t and the risk premium wedge D_t. Two types of industry-specific processes drive the industry technology $z_{i,t}$ and the relative demand for industry goods $\tilde{v}_{i,t}$. We assume that each shock follows an AR(1) process.

- Aggregate technology follows

$$\log(A_t) = \rho^A \log(A_{t-1}) + \epsilon_t^A, \qquad \epsilon_t^A \sim \mathcal{N}(0, \sigma_A^2) \tag{2.25}$$

- The risk premium shock follows

$$\log(D_t) = \rho^D \log(D_{t-1}) + \epsilon_t^D, \qquad \epsilon_t^D \sim \mathcal{N}(0, \sigma_D^2) \tag{2.26}$$

- The technology of industry i follows

$$\log(z_{i,t}) = \rho^z \log(z_{i,t-1}) + \epsilon_{i,t}^z, \qquad \epsilon_{i,t}^z \sim \mathcal{N}(0, \sigma_{z,i}^2) \tag{2.27}$$

- The relative demand for goods of industry i is normalized such that $\sum_{i=1}^I v_{i,t} = 1$ in each period,

$$v_{i,t} = \tilde{v}_{i,t} / \sum_{i=1}^{I} \tilde{v}_{i,t}. \tag{2.28}$$

  The exogenous processes $\tilde{v}_{i,t}$ follows

$$\log(\frac{\tilde{v}_{i,t}}{\nu_i}) = \rho^v \log(\frac{\tilde{v}_{i,t-1}}{\nu_i}) + \epsilon_{i,t}^v, \qquad \epsilon_{i,t}^v \sim \mathcal{N}(0, \sigma_{v,i}^2). \tag{2.29}$$

Since these four types of shocks play a central role in our analysis, let us briefly discuss their interpretation. We view the aggregate demand shock in the form of the risk premium wedge as a proxy for a variety of demand-side shocks. Demand-side shocks are typically characterized as disturbances that generate positive correlation between aggregate consumption, investment, output, and the price level. The risk premium wedge shares these characteristics and is similar in effect to several other shocks standard in the literature, such as monetary policy shocks, discount factor shocks, financial intermediation shocks and others.

The (positive) demand shock to industry i is characterised such that for a given level of prices, consumers prefer to consume more of good i, at the expense of the goods of other industries. As a consequence, the relative price of this good tends to rise, contrary to the industry-level technology shock. In the data, however, the increased demand might be a consequence of an increase in the quality of good i, in the case this is not correctly accounted for by the statistical office. Since our model can not distinguish between shifts in preferences and unaccounted quality improvements, it would identify both cases as demand shocks.

We model the technology process for individual industries as a combination of independent industry technology shocks and a common aggregate technology shock. In fact, the correlations between the technology processes across different industries might have a much more general structure. However, it is not possible to identify the general variance-covariance matrix using the short data series that we have available.[2]

[2] The estimated correlation matrix from a collection of T data points of n variables has rank smaller than or equal to $T - 1$. We work with 77 industries and the sample is 46 years, 25 in the pre-1984 subperiod.

2.2.8 Measurement errors

Hours in the model are subject to measurement errors. It is widely recognized that measuring hours worked is difficult, as it relies on survey information or administrative data, both of which are connected to well known issues, see e.g. Heathcote et al. (2014), Blundell et al. (2016). Moreover, adding the measurement errors also helps to bring the model closer to the data. Our model is quite parsimonious in terms of number of shocks, and as a consequence tends to generate too strong co-movement between variables. Measurement error shocks systematically reduce the correlations in the model, bringing them closer to the data.

In line with how we specified the rest of the shocks, the measurement error shock has an aggregate and an industry-specific component. We assume that measured hours in each industry follow

$$\log(h^m_{i,t}) = \log(h_{i,t}) + \epsilon^{ME}_{i,t} + \epsilon^{aME}_{t}, \tag{2.30}$$

where $\epsilon^{ME}_{i,t}$ is the idiosyncratic industry-level measurement error and ϵ^{aME}_{t} is the aggregate measurement error. We assume that measurement error shocks are i.i.d. normally distributed. Notice that, by affecting measured hours, the measurement errors indirectly affect measured labor productivity and measured total factor productivity as well.

2.2.9 Transmission of shocks between industries

Finally, we briefly describe the channels of transmission of the industry-specific shocks between industries in our model. These are similar to the mechanisms described in the existing literature (cf. section 2.1.1), apart from some modifications that arise because of nominal rigidity. The intuition is based on equation 2.18, which expresses the real marginal costs of an optimizing firm, and equation 2.7, which expresses the optimal demand for consumption of industry i good given its price.

The responses of the firms in industry i to shocks in their own industry are straightforward: a positive shock to technology drives down the real marginal costs, pushing down the prices of industry i's goods. A positive shock to demand in industry i increases the output of that industry, which creates an upward pressure on the prices of the industry's inputs and, subsequently, output. However, the price effect is relatively small, as the movement of production factors across industries in our model is relatively flexible. Even after a demand shock, measured productivity increases, due to the endogenous labor utilization and fixed costs.

A positive shock to technology in an upstream industry j, which provides either intermediate inputs or investment goods to sector i, decreases the real marginal costs in sector i, creating a negative pressure on its prices and boosting the output. Thus, output and measured productivity in sector i co-move with sector j. This channel has been thoroughly studied in the literature. In the New Keynesian model with price rigidities, the mechanism is somewhat dampened in comparison to the RBC setup where all prices adjust instantly. In contrast, a positive shock to demand in the upstream industry j has an adverse effect on industry i. As prices of industry j good increase with higher demand, industry i also faces higher input prices. Thus, its output and productivity fall.

Transmission of the shocks also happens in the opposite direction, from downstream industries upwards. A positive shock to demand in the downstream industry k, which buys intermediate inputs or investment goods from industry i, increases industry k's demand for production factors, effectively increasing the demand for goods of upstream industry i as well. Thus, the demand shock generates a positive co-movement between industries k and i. For a positive technology shock in downstream industry k, on the other hand, the effect on industry i is ambiguous in the short run. Due to the rigid prices, the demand for goods of industry k is quasi-fixed in the short run. Thus, the demand for production factors in industry k falls on impact, suppressing output and productivity in industry i. Later, as more and more firms in industry k are able to adjust their prices, the demand for industry k good grows, with the demand for industry i good also recovering.

2.3 Data and calibration

2.3.1 Data sources

The primary data source is the KLEMS growth accounting data set developed by Dale Jorgenson and his co-authors (Jorgenson 2008). The data set provides annual information on capital, labor and intermediate inputs and outputs of the U.S. economy between 1960 and 2005 disaggregated into 88 industries. The data set is unique in that it provides complete industry input-use tables including the corresponding price data for each year within the sample period. The annual tables provide the information necessary for calibrating the substitution elasticities in production and household demand. Additionally, we supplement the data set with the information from the BEA capital-flow table and the BEA input-use table (both 1992) to calibrate industry weights in investment and final consumption, respectively.

We focus on the private business sector which consists of 77 industries. We use the standard bottom-up KLEMS methodology in order to construct the aggregate series from the industry-level data, see e.g. Timmer et al. (2007a). The list of the industries, as well as the details describing the construction of data series and the moments are provided in appendix 2.B.

2.3.2 Measured productivity and output

The key to our analysis is the understanding of the various concepts of productivity as they are commonly used in the literature. Our model features a factor utilization margin, which is not observed in the data, fixed costs of production, firm profits and measurement errors. As a consequence, the standard Solow residual measures used in productivity accounting deviate from the exogenous technology in the model. At firm level, computing the Solow residuals following the methodology of the EU KLEMS database leads to

$$T\hat{FP}m_{i,t} = \hat{y}_{i,t} - s^K_{i,t}\hat{k}_{i,t} - s^L_{i,t}\hat{h}^m_{i,t} - s^M_{i,t}\hat{M}_{i,t}, \tag{2.31}$$

where s^X denotes the cost share of input X on gross output and hats denote growth rates of variables. We refer to residual $TFPm$ as the *measured productivity (TFP)*. On the other hand, the firm-level exogenous technology can be expressed in our model as

$$\hat{TFP}_{i,t} = \hat{A}_t + \hat{z}_{i,t} = \frac{y_{i,t}}{y_{i,t} + \Phi_i} \left[\hat{y}_{i,t} - \mu_{i,t}(s^K_{i,t}\hat{k}_{i,t} - s^L_{i,t}(\hat{h}_{i,t} + \hat{e}_{i,t}) - s^M_{i,t}\hat{M}_{i,t}) \right], \tag{2.32}$$

where Φ_i is the fixed cost and $\mu_{i,t}$ is the effective markup over the marginal costs.

Expressions 2.31 and 2.32 are only equal if the fixed costs are zero, prices are perfectly competitive, workers effort is constant over time and hours are measured precisely. Measured productivity reflects exogenous technology, but also fluctuations due to the unobserved effort, returns to scale and markups.

While we can easily distinguish the two measures of productivity in the model, it is very difficult to identify the *true* technology process $TFP_{i,t}$ in the data. The effective markup $\mu_{i,t}$, fixed costs Φ_i, and workers effort $e_{i,t}$ are not observable. Both inputs and output are subject to measurement issues. The data set reports the remuneration of production factors, but the capital share is pinned down as the residual. Therefore, firm profits are also included in the reported capital shares $s^K_{i,t}$.

Industry-specific real value added is defined in line with the growth accounting methodology in terms of growth rates as

$$\hat{va}_{i,t} = \frac{1}{s^{VA}_{i,t}} \left(\hat{y}_{i,t} - s^M_{i,t}\hat{M}_{i,t} \right), \tag{2.33}$$

and aggregate real value added follows the same definition using aggregate real gross output and aggregate intermediate inputs. Because the model abstracts from taxes, gross domestic product equals aggregate value added.

In line with most of the literature, we construct the growth rates of *aggregate measured productivity (TFP)* according to the KLEMS methodology using aggregate inputs and output[3]

$$\hat{TFPm}_t = \hat{VA}_t - s^K_t\hat{K}_t - s^L_t\hat{H}_t, \tag{2.34}$$

where s^K, s^L denote the cost share of capital resp. labor on value added, VA_t is aggregate value added, K_t is the aggregate capital and H_t are the aggregate hours. When comparing the data with the model-generated series, we compute measured productivity in the same way in both cases, using equations 2.31 and 2.34.

One should recognize that measures of productivity based on Solow residuals may reflect unobserved fluctuations in production inputs other than effort, most importantly composition effects and changes in capital utilization. Our data set is to some extent adjusted for endogenous variation in labor and capital composition. The measure of labor input reported in the data set is effective hours, defined as total hours adjusted for the composition of workforce, taking into account workers' education, age, and gender.

2.3.3 Calibration

We formulate the model at quarterly frequency and aggregate the simulated series to annual frequency in order to compare the model to our annual data. The baseline calibration aims to

[3] Our measure of aggregate TFP is value added-based, not gross output-based Solow residual. The difference between the two measures only affects the scaling of the productivity series.

reflect the U.S. economy over the period 1960-1984. We provide additional details on the calibration procedure in appendix 2.B and robustness checks in appendix 2.D.

Where possible and appropriate, we set model parameters to standard values from the literature. Following most of the New Keynesian literature, we solve the model by linearization around the zero inflation steady state. The discount rate β is set such that the implied interest rate is 4% annually. The annual capital depreciation rate δ is 10%. The capital adjustment cost parameter κ is calibrated such that the volatility of investment generated by the model is about 3.3 times higher compared to output, in line with the empirical evidence. The elasticity of substitution between firm goods within the same industry σ_I is set to imply a 10% markup, which is within the standard range. We calibrate the fixed costs Φ_i such that the firms make zero profits in steady state. The Taylor rule parameters γ_π and γ_r are set to 1.5 and 0.8, respectively. In the baseline calibration, the price stickiness θ_i is set to 0.75 in each industry, implying the average price adjustment frequency once a year. We set the consumption habit parameter χ to 0.5, towards the lower end in the DSGE literature.

The combination of the labor input elasticity σ_U and the effort elasticity parameter σ_e determines the wage elasticity of hours comparable to the standard Frisch elasticity in aggregate macroeconomic models. The parameter σ_U is calibrated conditional on σ_e, such that the implied Frisch elasticity is 0.5, within the range considered in the literature. More information about the mapping between the model parameters and the Frisch elasticity can be found in appendix 2.B.

The parameters of the model describing the industry-level structure of the economy are all chosen to match long-run averages in the data. In the production function, each of the intermediate input weights α_{ji} is set to match the long-run average cost share of intermediate inputs from industry j to industry i in the Jorgenson data set. The industry-specific factor weights $\mu_{K,i}$, $\mu_{L,i}$, and $\mu_{M,i}$ are set to match the industry i's cost shares of capital, labor, and intermediate inputs, again using the long-run averages from the Jorgenson data set. The investment good composition weights ξ_i are set to match the cost shares of investment from the 1992 BEA capital-flow table. As the model only features one type of investment, we use the average composition across all industries to calibrate weights ξ_i. Regarding the household preferences, the consumption composition weights ν_i are set to match the cost shares of consumption from the 1992 BEA input-use table. The industry-specific preference parameters for supplying labor across different industries η_i are chosen such that in steady state, the allocation of labor supply across industries matches the long-run average industry composition in the data, conditional on average industry wages, cf. the intra-temporal labor supply first order condition 2.49.

The remaining parameters of the model consist of the substitution elasticities in the production process, consumption, and labor supply (σ_y, σ_M, σ_X, σ_C, σ_N and σ_e), the variances of the shocks to technology (σ_A^2 and $\sigma_{z,i}^2$), to demand (σ_D^2 and $\sigma_{v,i}^2$), and of the measurement error. Out of these parameters, the elasticities σ_y, σ_M are calibrated directly to match specific data targets, see the discussion below. The rest of the parameters are calibrated using indirect inference, within a two-step procedure which targets a relevant set of moments. In the inner loop of the procedure, we determine the variances of all shocks conditional on the elasticity parameters. The variances of the measurement error shocks are calibrated to generate an ex-ante given share of aggregate

Calibration summary			
Parameter	Symbol	Value	Target/Source
Elasticities			
Intra-industry substitution	σ_I	11	10% markup
Production factors subst.	σ_y	0.39	price elasticity of production factors
Intermediate inputs subst.	σ_M	0.75	price elasticity of intermediate inputs
Consumption good subst.	σ_C	0.38	price elasticity of industry gross output
Investment good subst.	σ_X	0.38	equals σ_C
Total labor input	σ_U	1.1	Frisch elasticity 0.5
Industry labor input subst.	σ_N	7.9	mean volatility of industry hours
Effort	σ_e	1.9	correlation productivity and hours
Hours	σ_h	1	normalization
Cost shares			
Production factor weights	$\mu_{i,\times}$		cost shares Jorgenson database, average
Intermediate inputs weights	α_{ji}		cost shares Jorgenson database, average
Consuption weights	ν_i		1992 BEA input-use table
Investment good weights	ξ_i		1992 BEA capital flow table
Fixed costs	Φ_i		zero profits in steady state
Shock processes			
Aggregate technology, volatility	σ_A		SMM objective
Industry technology, volatility	$\sigma_{z,i}$		SMM objective
Aggregate demand, volatility	σ_D		SMM objective
Industry demand, volatility	$\sigma_{v,i}$		SMM objective
Agg. measurement error, volatility	σ_{aME}		20% variance of agg. measured hours
Ind. measurement error, volatility	$\sigma_{ME,i}$		25% variance of ind. measured hours
Autocorrelation, structural shocks	$\rho^{\times}$	0.95	standard
Other			
Discount factor	β	0.96	standard (annual)
Capital depreciation	δ	10%	standard (annual)
Consumption habit	χ	0.5	standard
Taylor parameter	γ_π	1.5	standard
Taylor rule smoothing	γ_r	0.8	standard
Adjustment cost capital	κ	20	relative volatility of investment
Price stickiness	θ_i	0.75	standard
Industry weight labor disutility	η_i		industry hours/wages in steady state
Effort weight in labor disutility	Λ_i		normalization effort in steady state

Table 2.1: Calibration summary

and industry fluctuations. The variances of the structural shocks are estimated using simulated method of moments. In the outer loop, the elasticities σ_X, σ_C, σ_N and σ_e are calibrated such that they jointly match a set of three moments with one additional identifying assumption.

Comparatively little attention has been given to estimating the elasticities of substitution between factor inputs and between industry-specific goods in the macro literature in recent decades, although they influence the way in which the economy responds to the various types of shocks, see Atalay (2017) for discussion. We believe that the calibration of the elasticities σ_y, σ_M, σ_C, σ_X, and σ_N is one of the useful contributions of our paper. Our model is parsimonious in that the elasticities are the same across all industries. Therefore, we have a relatively small set of parameters that we estimate using a large number of industry-level series in the outer loop. We choose the method of moments over maximum likelihood methods, because it allows a better interpretation of which data features determine the values of the individual parameters. Table 2.1 shows an overview of the model parameters and calibration targets.

Elasticities: identifying moments

In this section we briefly discuss which moments in the data identify the individual elasticity parameters. We calibrate the production function parameters σ_y and σ_M directly from the estimated elasticity of the corresponding input shares to the changes in the relative prices. For the elasticity of substitution between production factors σ_y, the first order condition 2.62 implies that for each model industry i,

$$d\ln\left(\frac{M_{i,t}P^M_{i,t}}{l_{i,t}w_{i,t}}\right) = (\sigma_y - 1)d\ln\left(\frac{w_{i,t}}{P^M_{i,t}}\right). \tag{2.35}$$

We use the industry-level information about prices and volumes from the Jorgenson data set and regress the changes in the cost shares (left-hand side of equation 2.35) on the changes in the relative prices (right-hand side) industry by industry. We use the average across the I industry coefficients to pin down the value of σ_y.

For the elasticity of substitution between intermediate inputs from various industries σ_M, we use the same approach based on the first order condition 2.56. We compute the regression coefficient for each pair of intermediate inputs supplied into each production industry i. We use the average over all estimates to pin down the value of σ_M. The Jorgenson data set is unique in that it provides the information about the prices and volumes of the production inputs at the required level of disaggregation and across the longer time period. The values of σ_y and σ_M are broadly in line with the existing estimates, cf. Atalay (2017).

There are no model equations that directly map the remaining elasticity parameters σ_C, σ_X, σ_N and σ_e to the available data. Thus, these parameters are calibrated simultaneously in the outer loop of the calibration procedure using a set of three targets and one additional identifying assumption. However, each of the targeted moments identifies one of the parameters in an intuitive way. The parameters σ_C and σ_X both influence the reaction of the industry output shares to the changes in relative prices. As we do not have any information that distinguishes the impact of the two elasticities, we assume σ_C and σ_X are equal and target the average responsiveness of the relative industry output cost shares to relative prices. We target the statistic $\hat{\eta}^y$, computed as the average across industry-pair regression coefficients from the equation

$$d\ln\left(\frac{y_{i,t}p_{i,t}}{y_{j,t}p_{j,t}}\right) = \eta^y_{i,j} \cdot d\ln\left(\frac{p_{j,t}}{p_{i,t}}\right). \tag{2.36}$$

The elasticity of substitution between working in different industries σ_N influences the volatility of industry-level hours. We use the mean volatility of industry hours relative to the volatility of aggregate hours as the second target in the outer loop. The resulting value of $\sigma_N = 7.9$ implies high mobility of labour force across industries.

One of the essential elements of our model is the endogenous factor utilization. The elasticity of unobservable effort relative to hours is determined by parameter σ_e. A more elastic effort implies that measured productivity fluctuates more with hours and, everything else equal, the two variables are more correlated.[4] Thus, we identify σ_e by targeting the correlation between aggregate hours and measured productivity in the pre-1984 period. This is the only aggregate correlation that we target in the calibration procedure. The resulting value of $\sigma_e = 1.9$ implies that for a one percent increase in hours worked, the effective labor input increases by roughly 1.5%. The value

[4] See Molnárová (2020) for discussion.

Relative standard deviations					
	Data	Industry shocks		Aggregate shocks	
		technology	demand	technology	demand
$\sigma(\hat{TFP}^m)/\sigma(\hat{VA})$	0.62	0.89	$\times$	0.93	0.48
$\sigma(\hat{H}^m)/\sigma(\hat{VA})$	0.83	0.26	$\times$	0.12	0.76
$\bar{\sigma}(\hat{tfp}_i^m)/\bar{\sigma}(\hat{y}_i)$	0.50	1.87	0.19	0.60	0.19
$\bar{\sigma}(\hat{y}_i)/\sigma(\hat{Y})$	1.96	1.87	15.2	1.16	1.13
$\bar{\sigma}(\hat{tfp}_i^m)/\sigma(\hat{TFP}^m)$	1.86	3.11	14.0	0.53	0.62

Table 2.2: Relative standard deviations of variables generated by each type of the shock separately. The first column shows the ratios of standard deviations measured in the data while columns 2 - 5 show the corresponding ratios generated by each type of shock in the model. For industry variables, $\bar{\sigma}(\cdot)$ denotes average across industry standard deviations. All variables are expressed in growth rates.

of σ_e is in line with the existing literature. Basu et al. (2006) estimate that, including the factor utilization, a one percent increase in measured hours is associated with an increase of effective labor input between 2.1% (nondurable manufacturing) and 0.64% (non-manufacturing industries).

Shock variances

The main exercise of this paper is the estimation of variances of the exogenous shocks and their contribution to business cycle fluctuations. We jointly estimate the variances of the two aggregate shocks (σ_A^2 and σ_D^2) and two times I industry-specific shocks ($\sigma_{z,i}^2$ and $\sigma_{v,i}^2$) using the generalized simulated method of moments. We use three aggregate and $2 \times I$ industry-level variances in the SMM objective function. At the aggregate level, we target the variances of aggregate measured productivity, value added and hours. At the industry level, we target the variance of industry measured productivity and of industry gross output.[5] The resulting variances are the solution of a quadratic problem with inequality constraints, as all variances must be greater or equal to zero.

In order to provide some intuition on which data features identify the composition of the shocks in the model, we simulate the model four times, each time allowing for shocks of only one type. Table 2.2 displays the relative standard deviations for the set of variables that enter the SMM objective. The first column shows the data, while columns 2 - 5 report model simulations, each column generated by only one type of shock.[6] For the industry variables, the table reports simple averages of standard deviations across all industries.

The main insight from table 2.2 is that the different types of shocks generate different sets of second moments, such that the variances of the shocks are well identified. The relative importance of aggregate versus industry shocks is identified because the industry shocks generate higher volatilities of industry-level variables compared to the aggregate variables. This is not true for the aggregate shocks, cf. the last two rows of table 2.2. The volatility of the aggregate demand shock relative to technology shocks is pinned down by (each of) the first two rows of table 2.2. The first line shows that technology shocks, both on the aggregate and the industry level, generate fluctuations in aggregate measured productivity of almost the same size as that of aggregate value

[5] Notice that we do not include the variance of industry-level hours. The choice of the elasticity parameter σ_N in the outer loop pins down their average variance.

[6] In the case of industry shocks, we keep the variances of shocks across industries the same as in our baseline calibration.

added, while the aggregate demand shock generates much smaller relative fluctuations. The second line displays the relative standard deviation of aggregate hours. In this case it is the demand shocks that generate large fluctuations, while technology shocks do very little.[7] Thus, in order to match the relative volatilities of the aggregate variables, the model clearly needs aggregate demand shocks. Subsequently, as the relative size of aggregate demand shocks is determined by the relative volatilities of the aggregate variables, the information in the last two rows pins down the weight of the aggregate shock to technology relative to the industry-specific shocks. Lastly, the relative importance of the two industry-level shocks follows from the relative size of industry-level fluctuations in measured productivity and output, which is shown in the third row. Besides the three relative shock variances determined by the information in table 2.2, the absolute size of fluctuations is pinned down by the size of the fluctuations in the data.

One should point out that for industry variables, table 2.2 displays average standard deviations across all industries. In fact, we estimate the industry shock variances separately for each industry. Nevertheless, the identification logic described above works analogously for each industry individually. Due to the over-identification in the SMM procedure and the non-negativity constraint on variances, the targets are not matched precisely.

The variances of the measurement errors are calibrated to generate given shares of aggregate and industry measured hours, for discussion see e.g. Boivin and Giannoni (2006), Justiniano et al. (2013). The measurement errors are set to explain 20% of the variance of the aggregate hours and 25% of the variance of the industry hours. The measurement error shocks are not essential for our main results, namely that there are no aggregate technology shocks and that cyclicality of aggregate measured productivity decreases with smaller aggregate demand shocks. However, omitting the measurement error increases the co-movement between variables above what we observe in the data, see robustness checks in appendix 2.D.

Alternative calibration for post-1984 period

The baseline model calibration targets the data moments from the pre-1984 period. In the second exercise we change the variance of the aggregate demand shocks and compare the model results to the data in the period after 1984. This is motivated by the fact that several authors, for example Barnichon (2010) and Galí and Gambetti (2009), have suggested that the great moderation period was characterised by a different composition of shocks, especially stressing the smaller shocks to aggregate demand, or muted effects of these shocks on the economy. We keep the rest of the parameters, including the variances of the other shocks, the same as in the baseline. This is because the aim of the exercise is to show to which extent a decrease in the volatility of the aggregate demand shocks can explain the changes in the co-movement patterns observed after 1984. It is not our ambition to precisely identify the decrease in the volatility of the aggregate demand shocks.

In order to pin down the alternative variance of the aggregate demand shock, we notice that the shock composition in the model has strong implications for the correlation between the aggregate hours and value added. Decreasing the volatility of the aggregate demand shock

[7] The weak response of hours to tech shocks is typical for New Keynesian models, see e.g. Galí (1999).

reduces this correlation. We choose this moment to discipline the exercise and decrease the variance of the shock such that the implied reduction in the correlation between the aggregate hours and value added is 17 p.p., which equals the reduction between the pre- and post-1984 samples in the data. Using this criterion, the volatility σ_D decreases by around 40%, in line with the change identified in the existing literature; see e.g. Barnichon (2010). As a further evidence that this decrease in volatility of the aggregate shock σ_D is reasonable, we observe that the alternative calibration generates a reduction in the standard deviation of value added from the pre-1984 value of 0.026 to the post-1984 value of 0.017, which is very close to the data.

2.4 Results

2.4.1 Model fit

In this section we show that the baseline calibration of the model fits the data very well in many dimensions. Tables 2.3, 2.4 and 2.5 compare sets of second moments in the data and generated from the model simulations. We mark the moments that we directly or indirectly used as calibration targets in bold. As the number of targets is bigger than the number of free parameters, the targets are not necessarily matched exactly. The top panel of each table displays the results for the baseline calibration and compares them to the data for pre-1984 period. The bottom panels show the results for the post-1984 period, which we discuss in section 2.4.5.

The top panel of table 2.3 displays standard deviations of aggregate variables relative to aggregate value added (or GDP), as well as their correlations with value added and with measured productivity. Our model provides a good match for all aggregate moments, with one notable exception. The model generates highly procyclical inflation, i.e., a strong Phillips curve characteristic for New Keyesian models. In contrast, inflation is basically acyclical in the data, which contain the stagflation period of the 1970s.

Table 2.4 summarizes the same information at the industry level. As the moments vary across industries both in the model and in the data, we report weighted averages of the second moments across the industries. The top panel of table 2.4 shows that the model fit is satisfactory at the industry-level as well. Average correlations of the industry variables with value added and measured productivity are well in line with the data for all variables. Average relative standard deviations are close to their data counterparts, once again with one exception. The volatility of prices at the industry level is substantially higher in the data than in the model. The possible explanations are that the model is missing pricing (markup) shocks, or that it does not reflect the measurement error in price data. The alternative version of the model with flexible prices, which we discuss in section 2.4.4, demonstrates that the low volatility of industry prices is not just a consequence of price rigidity in the model. Despite of the low volatility, the negative correlation between relative prices and value added at the industry level is an important confirmation that the model features a reasonable ratio of demand and supply-side shocks at the industry level.

Lastly, table 2.5 documents the co-movement between industries. For each industry-level variable we compute a correlation between each pair of industries. The table reports the unweighted mean of these 2926 pairwise correlations. The model does a good job in matching the average

Aggregate variables: second moments									
	Standard dev. relative to value added*			Correlations with value added			Correlations with measured TFP		
	Data	(SE)	Model	Data	(SE)	Model	Data	(SE)	Model
Baseline calibration									
Value added	*0.027*	(0.00)	***0.026***	1.00	(0.00)	1.00	0.85	(0.06)	0.87
Gross output	1.17	(0.05)	1.32	0.98	(0.00)	0.98	0.80	(0.08)	0.82
Measured TFP	0.62	(0.03)	**0.59**	0.85	(0.06)	0.87	1.00	(0.00)	1.00
Hours	0.83	(0.07)	**0.81**	0.86	(0.03)	0.83	0.49	(0.12)	**0.49**
Intermediate inputs	1.37	(0.09)	1.68	0.95	(0.01)	0.95	0.74	(0.08)	0.77
Inflation	0.93	(0.08)	1.01	0.14	(0.17)	0.92	-0.11	(0.24)	0.72
Labor productivity	0.51	(0.05)	0.54	0.56	(0.13)	0.58	0.89	(0.03)	0.88
Int. inputs per hour	0.77	(0.05)	1.04	0.76	(0.03)	0.88	0.80	(0.03)	0.87
Investment	-	-	3.29	-	-	0.97	-	-	0.83
Consumption	-	-	0.35	-	-	0.66	-	-	0.64
True TFP	-	-	0.27	-	-	0.18	-	-	0.40
Post-1984 calibration									
Value added	*0.016*	(0.00)	*0.017*	1.00	(0.00)	1.00	0.47	(0.18)	0.80
Gross output	1.20	(0.13)	1.25	0.90	(0.02)	0.96	0.26	(0.23)	0.71
Measured TFP	0.72	(0.07)	0.72	0.47	(0.18)	0.79	1.00	(0.00)	1.00
Hours	1.25	(0.20)	0.87	0.70	(0.04)	**0.66**	-0.26	(0.16)	0.11
Intermediate inputs	1.62	(0.25)	1.58	0.74	(0.07)	0.89	0.07	(0.23)	0.61
Inflation	1.51	(0.19)	0.93	0.11	(0.08)	0.82	0.05	(0.22)	0.51
Labor productivity	0.90	(0.13)	0.77	0.14	(0.17)	0.53	0.89	(0.01)	0.92
Int. inputs per hour	1.08	(0.12)	1.10	0.29	(0.17)	0.74	0.41	(0.10)	0.79
Investment	-	-	3.18	-	-	0.95	-	-	0.73
Consumption	-	-	0.44	-	-	0.66	-	-	0.62
True TFP	-	-	0.40	-	-	0.40	-	-	0.59

Table 2.3: Comparison of selected second moments in the model and in the data, growth rates of aggregate variabes. Top panel: baseline calibration contrasted to the data in the pre-1984 period. Bottom panel: calibration with lower volatility of the aggregate demand shock compared to the post-1984 data. The values that are targeted in the calibration procedure are marked in bold. Bootstrapped standard errors (SE).
*except of standard deviation of value added.

Industry variables: averages across second moments									
	Standard dev. relative to value added*			Correlations with value added			Correlations with measured TFP		
	Data	(SE)	Model	Data	(SE)	Model	Data	(SE)	Model
Baseline calibration									
Value added	*0.088*	(0.01)	*0.074*	1.00	(0.00)	1.00	0.78	(0.01)	0.81
Gross output	0.71	(0.00)	0.84	0.84	(0.01)	0.88	0.57	(0.01)	0.55
Measured TFP	0.36	(0.01)	0.38	0.78	(0.01)	0.81	1.00	(0.00)	1.00
Hours	0.56	(0.02)	**0.60**	0.38	(0.02)	0.46	-0.02	(0.03)	-0.06
Intermediate inputs	0.83	(0.01)	0.92	0.35	(0.04)	0.58	0.14	(0.02)	0.18
Prices	0.66	(0.03)	0.25	-0.33	(0.01)	-0.36	-0.43	(0.02)	-0.54
Input prices	0.33	(0.04)	0.11	-0.13	(0.02)	-0.15	-0.16	(0.02)	-0.21
Labor productivity	0.95	(0.04)	0.86	0.72	(0.01)	0.72	0.84	(0.01)	0.94
Int. inputs per hour	0.73	(0.02)	0.52	0.17	(0.04)	0.48	0.22	(0.04)	0.38
True TFP	-	-	0.36	-	-	0.44	-	-	0.73
Post-1984 calibration									
Value added	*0.097*	(0.01)	*0.070*	1.00	(0.00)	1.00	0.76	(0.03)	0.79
Gross output	0.47	(0.00)	0.79	0.84	(0.00)	0.87	0.53	(0.03)	0.51
Measured TFP	0.30	(0.01)	0.40	0.76	(0.03)	0.79	1.00	(0.00)	1.00
Hours	0.43	(0.01)	0.59	0.28	(0.02)	0.36	-0.23	(0.04)	-0.20
Intermediate inputs	0.58	(0.03)	0.84	0.43	(0.01)	0.50	0.12	(0.03)	0.06
Prices	0.83	(0.19)	0.26	-0.41	(0.01)	-0.38	-0.46	(0.01)	-0.54
Input prices	0.25	(0.03)	0.11	-0.10	(0.03)	-0.14	-0.11	(0.04)	-0.20
Labor productivity	1.03	(0.13)	0.91	0.68	(0.03)	0.73	0.90	(0.01)	0.95
Int. inputs per hour	0.52	(0.02)	0.47	0.20	(0.02)	0.37	0.34	(0.02)	0.33
True TFP	-	-	0.38	-	-	0.49	-	-	0.75

Table 2.4: Comparison of selected second moments in the model and in the data, growth rates of industry variables. Reported numbers are averages (weighted by industry output) across industry moments. Top panel: baseline calibration contrasted to the data in the pre-1984 period. Bottom panel: calibration with lower volatility of the aggregate demand shock compared to the post-1984 data. The values that are targeted in the calibration procedure are displayed in bold. Bootstrapped standard errors (SE).
*except of standard deviation of value added.

Cross-Industry Correlations			
	Data	(SE)	Model
Baseline calibration			
Value added	0.14	(0.009)	0.13
Gross output	0.22	(0.015)	0.30
Measured TFP	0.05	(0.008)	0.07
Hours	0.20	(0.011)	0.20
Intermediate inputs	0.19	(0.035)	0.36
Output price	0.07	(0.015)	0.01
Input price	0.15	(0.017)	0.21
Labor productivity	0.02	(0.006)	0.04
Int. inputs per hour	0.07	(0.012)	0.40
True TFP	-	-	0.00
Post-1984 calibration			
Value added	0.11	(0.011)	0.07
Gross output	0.19	(0.011)	0.18
Measured TFP	0.06	(0.009)	0.04
Hours	0.25	(0.047)	0.12
Intermediate inputs	0.22	(0.020)	0.20
Output price	0.18	(0.037)	0.01
Input price	0.29	(0.055)	0.21
Labor productivity	0.07	(0.012)	0.04
Int. inputs per hour	0.09	(0.029)	0.24
True TFP	-	-	0.00

Table 2.5: Comparison of average cross-industry correlations in the model and in the data, growth rates of industry variables. Reported numbers are simple averages across pairwise industry correlations. Top panel: baseline calibration contrasted to the data in the pre-1984 period. Bottom panel: calibration with lower volatility of the aggregate demand shock compared to the post-1984 data. Bootstrapped standard errors.

cross-industry correlations of most variables. The co-movement in the intermediate inputs used by the industries is slightly exaggerated. As a consequence, gross output across industries also co-moves more than in the data.

Of the many results reported in tables 2.3 - 2.5, we want to highlight several aspects. First, the correlations of all real aggregate variables with value added and with measured productivity are in line with the data. Moreover, the correlations of industry variables with industry value added and measured productivity are also matched well. Second, the model fits well the relative standard deviations of the variables. Noticeably, the model replicates the fact that gross output fluctuates more than value added at the aggregate level, but less than value added at the industry level. We further discuss this property in section 2.4.4. Third, the model does a good job in matching the average cross-industry correlations of most variables, although we do not target any of them. In particular, the average cross-industry correlations of measured productivity and of labor productivity are small, although significantly different from zero. In the next section we show that all technology shocks in the model are idiosyncratic industry-level shocks, and the positive correlation is generated by the aggregate demand shocks through endogenous effort and, to a smaller extent, due to increasing returns to scale.

2.4.2 What shocks are driving business cycle fluctuations?

Table 2.6 shows the variance decomposition of selected model variables. The most striking observation is that our model implies zero role for aggregate technology shocks. Technology shocks

Variance Decomposition					
	Aggregate shocks		Industry shocks		Measurement
	technology	demand	technology	demand	error
Industry variables					
Value added	0.00	0.18	0.28	0.54	0.00
Gross output	0.00	0.35	0.05	0.60	0.00
Measured TFP	0.00	0.07	0.75	0.11	0.07
Hours	0.00	0.22	0.13	0.40	0.25
Intermediate inputs	0.00	0.42	0.14	0.44	0.00
Output price	0.00	0.05	0.94	0.01	0.00
Input price	0.00	0.05	0.94	0.01	0.00
Labor productivity	0.00	0.05	0.65	0.18	0.12
True TFP	0.00	0.00	1.00	0.00	0.00
Aggregate variables					
Value added	0.00	0.88	0.12	0.00	0.00
Gross output	0.00	0.95	0.04	0.01	0.00
Measured TFP	0.00	0.59	0.26	0.00	0.15
Hours	0.00	0.78	0.02	0.00	0.20
Intermediate inputs	0.00	0.96	0.02	0.02	0.00
Inflation	0.00	0.99	0.01	0.00	0.00
Labor productivity	0.00	0.20	0.35	0.00	0.45
Int. inputs per hour	0.00	0.81	0.03	0.05	0.12
Investment	0.00	0.92	0.08	0.00	0.00
Consumption	0.00	0.50	0.45	0.05	0.00
True TFP	0.00	0.01	0.99	0.00	0.00

Table 2.6: Variance decomposition of selected model variables, baseline calibration.

are present in the model, but all of them are industry-specific.

The top panel of table 2.6 displays the decomposition for the industry-level variables. Not surprisingly, for all industry-level variables, the majority of the fluctuations is explained by the industry-specific shocks: industry demand shocks explain about a half of the fluctuations of industry-level value added and production inputs (capital, hours, intermediate inputs). On the other hand, shocks to technology are especially important for measured productivity and prices. Due to the high flexibility of factors across industries, industry relative prices react very little to an increased demand for the industry good.

The bottom panel of table 2.6 displays the variance decomposition for the aggregate variables. In this case, the effect of the industry-specific shocks is considerably smaller. The industry demand shocks do not contribute to aggregate fluctuations by construction, and industry shocks to technology wash out to a large extent. The majority of the fluctuations of the aggregate variables, including measured TFP, is explained by aggregate shocks to demand, due to endogenous effort and returns to scale, as we described in the previous sections. Fluctuations in hours are driven almost exclusively by demand shocks, but observed hours are by assumption also subject to sizeable measurement errors.

To the best of our knowledge, we are the first ones to attribute zero role to the aggregate technology shock in this class of models. Why do we come to different conclusions than the previous literature? In their seminal contribution, Foerster et al. (2011) estimate that idiosyncratic industry-specific shocks are responsible for 20% to 50% of the aggregate fluctuations in industrial production, depending on the sample period. The remaining fluctuations of aggregate variables in their model, as well as in multiple other contributions, are explained by an exogenous common factor that drives productivity, i.e., aggregate technology shock.

The reason why the existing literature assigned a big part of the fluctuations to the aggregate component of the technology shocks is that it is hard to generate the co-movement in measured productivity observed in the data from *independent* industry-level shocks only. Even though the average correlation of 0.05 in table 2.5 appears small, the aggregate component necessary to generate the co-movement turns out to be powerful enough to explain a major part of the aggregate fluctuations.[8] This is also true in our model. However, in our model the co-movement between measured productivity across industries can also arise from aggregate demand shocks.

Digging a bit deeper, we can describe how the individual mechanisms in our model alter the previous results. On the one hand, our model includes features that further reduce the role of industry technology shocks in comparison to the previous literature. First, the model includes industry demand shocks which explain a substantial part of the fluctuations at the industry level. Second, prices in the model are rigid, which suppresses the transmission of shocks across industries, cf. section 2.2.9. Both features imply that an even larger part of aggregate productivity fluctuations remains to be explained by aggregate shocks. However, in contrast to the literature, we do not assume that these aggregate shocks must be technology shocks. Table 2.3 shows that the standard deviation of growth in aggregate "true" technology, arising purely from technology shocks, is indeed less than half of the standard deviation of measured TFP. Put in another way, technology shocks in our model explain only about one fourth of the variance of aggregate measured TFP. As it turns out, industry technology shocks are sufficiently large to generate this part. The rest is generated by the changes in aggregate demand through endogenous factor utilization.

2.4.3 Moments within and across industries

Given the importance of the industry-level moments for the identification of shocks in our model, it is important to test whether the model generates a good fit across the individual industries. Therefore, we complement the industry-level averages reported in tables 2.4 and 2.5 with the information about the distribution of the moments across industries.

Industry-level second moments Figure 2.1 shows the distribution of the key industry-level moments across the 77 industries. Each plot compares the distribution in the data to the *population* distribution generated by the model under the baseline calibration. The population distribution depicts the industry moments averaged over a large number of simulations. The standard deviations of both distributions are reported in table 2.7.

All four moments display a large variation across industries, comparable between the data and the model. The model fits the distribution of the volatilities of measured TFP and gross output (top panels) almost perfectly, because the individual volatilities are targeted in the calibration procedure. For correlations of measured productivity with value added and hours (bottom panels

[8] To illustrate this point with a simple example, let us assume industries are symmetric, and aggregate (growth rate) variable X can be expressed using industry variables as $X = \sum_{i=1}^{I} \frac{1}{I} x_i$. Standard deviation of variable x_i in each industry is the same (equal σ) and pairwise correlation is the same for each pair of industries (equal c).

$$var(X) = \frac{1}{I^2} \sum_{i=1}^{I} \sum_{j=1}^{I} cov(x_i, x_j) = \frac{1}{I^2} \sum_{i=1}^{I} var(x_i) + \frac{1}{I^2} \sum_{i \neq j} corr(x_i, x_j) std(x_i) std(x_j) = \frac{1}{I}\sigma^2 + \frac{I-1}{I}\sigma^2 c$$

For $I = 77$ industries and the average correlation $c = 0.05$, the contribution of the off-diagonal elements to the aggregate variance is around 4 times bigger than that of the diagonal elements.

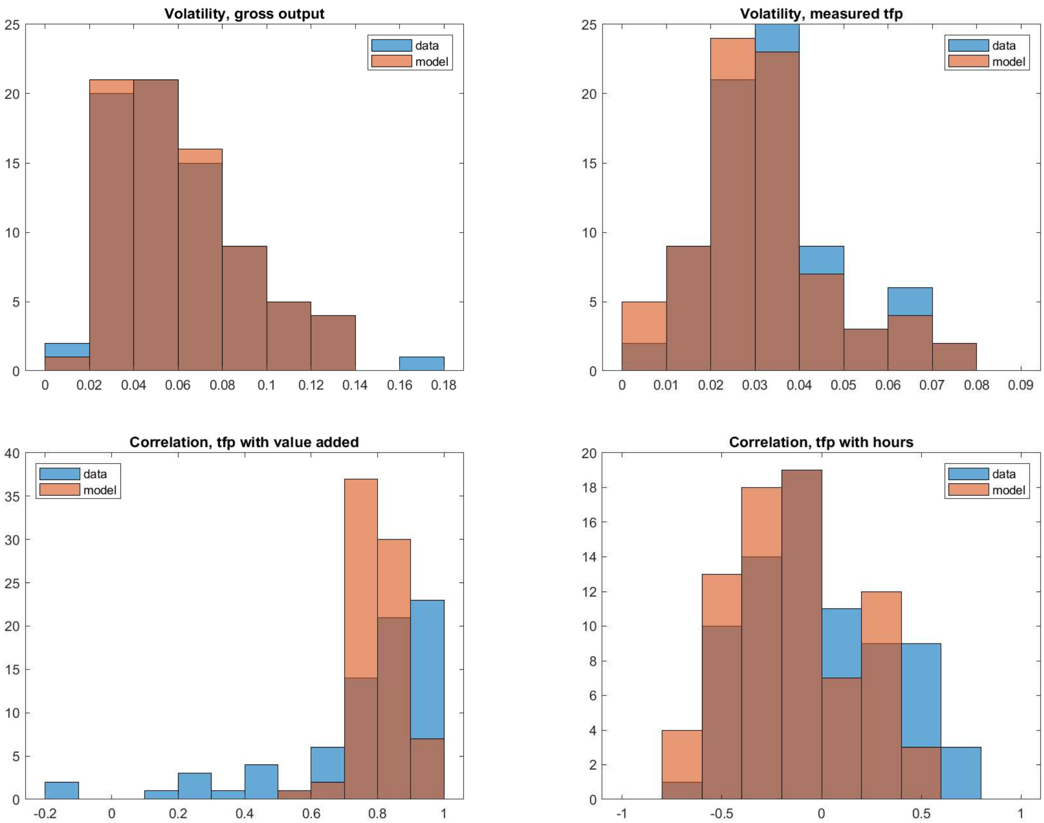

Figure 2.1: Distribution of industry-level second moments in the data and generated by the model. Baseline calibration. Top panel: volatility of gross output (left) and measured tfp (right). Bottom panel: correlation of measured tfp with output (left) and measured hours (right). The volatilities in the top panel are targeted in the SMM. The correlations in the bottom panel are results.

Distribution of within-industry and cross-industry correlations					
	Average correlation		Standard deviation (distribution)		
	Data	Model	Data	Model sampling	Model population
Within-industry correlations					
corr(va_i, $tfpm_i$)	0.76	0.80	0.24	0.11	0.07
corr(h_i, $tfpm_i$)	-0.03	-0.14	0.33	0.37	0.32
Cross-industry correlations					
Value added	0.14	0.13	0.29	0.25	0.15
Gross output	0.22	0.30	0.28	0.27	0.20
Measured TFP	0.05	0.07	0.27	0.22	0.07
Hours	0.20	0.20	0.29	0.23	0.12

Table 2.7: Distributions of within-industry and cross-industry correlations. Data, model population distribution, and (average) sample distributions. All averages are computed as simple means.

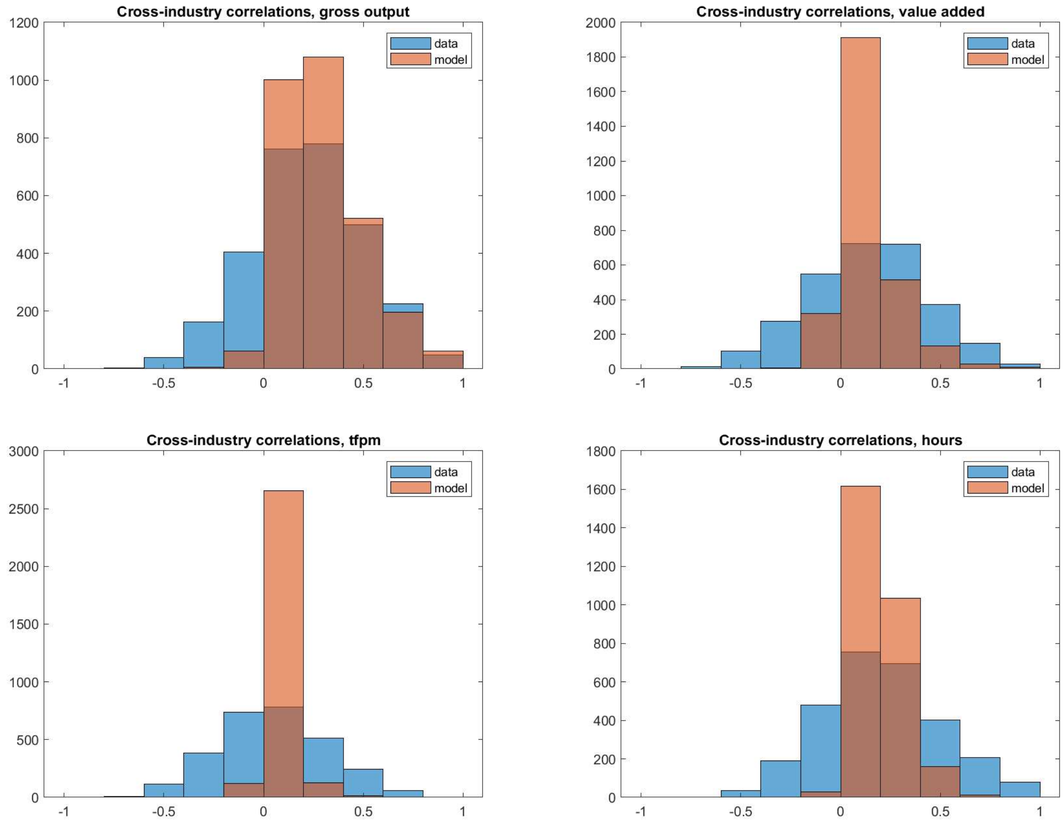

Figure 2.2: Histograms of pairwise cross-industry correlations of selected macroeconomic variables in the data and generated by the model. Baseline calibration, population distribution generated by the model.

of figure 2.1), the model generates a population distribution that is more concentrated compared to the data. In particular, the model completely misses a handful of industries with very low correlations between measured productivity and output. However, we have to consider that the data distribution contains sizeable sampling error, which is not reflected in the population distribution from the model.

To account for the sampling error, table 2.7 also reports the average standard deviation of the distributions generated in short model simulations, cf. column *model sampling*. Accounting for the sampling error brings the distribution of the model correlations closer to the data, although it can not generate the fat tail for the correlation between measured productivity and output.

Co-movement across industries We discussed the importance of the co-movement between industries for the aggregate fluctuations and displayed average cross-industry correlations in table 2.5. Figure 2.2 shows the distribution of the cross-industry correlations across the 2926 industry-pairs for four industry variables.

In all four cases, the correlations in the data are very dispersed. The bottom left panel plots the cross-industry correlations of measured total factor productivity, which range between -0.5 and 0.7. The average correlation is 0.05. The model generates a much more concentrated population distribution, which is also true for the other displayed variables. To account for sampling error, the bottom panel of table 2.7 again reports standard deviation for both long simulation (population distribution) and average across short model simulations (model sampling). While the heterogeneity in the population moments falls short of the data by a considerable margin, the typical distribution of a short model simulation displays a dispersion that is close to the one observed in the data.

In sum, the distributions generated by the model lend further credibility to our results. Despite a lot of symmetry imposed on the model industries, such as identical substitution elasticities and degree of price rigidity, the model generates a realistic level of industry-level heterogeneity.

2.4.4 Discussion of alternative modelling choices

The natural question is whether the results presented in sections 2.4.1 and 2.4.2 are robust, and how they compare with alternative model specifications. To make the main mechanisms driving the results more transparent, and to provide an intuition on which aspects of the data identify the model, we compare our baseline calibration against what we think are the two most relevant alternatives. First, endogenous effort explains most of the aggregate fluctuations in measured productivity, and thereby "crowds out" the aggregate technology shocks from our model. Thus, we re-calibrate a version of the model with constant effort and point out the dimensions in which this version does not fit the data. Second, we calibrate a version of the model with perfectly flexible prices, which is more comparable to the RBC-style industry-level models in the literature. For each alternative, we recalibrate the variances of all shocks. Detailed results for the two alternative versions of the model are available in appendix 2.D.

Tables 2.8–2.11 present the results for the alternative model with constant effort. We recalibrate the variances of the shocks, while the remaining structural parameters are kept the same as in the baseline. In the absence of endogenous effort, our model assigns a substantial role to aggregate technology shocks, which explain 75 percent of the variance of aggregate measured TFP. However, aggregate technology shocks contribute very little to the fluctuations of aggregate hours, which are explained by demand shocks.

This version of the model calibration fails to match the data in several important ways. Most obviously, the model grossly overestimates the average cross-industry correlation of both measured TFP and of labor productivity. Aggregate technology shocks generate almost as much co-movement in measured productivity as in value added, at odds with the data: the cross-industry correlation of measured TFP increases to 0.13, compared to 0.05 in the data. Second, the model is not able to generate a positive correlation between aggregate hours and measured productivity. Both in New Keynesian models and empirically, technology shocks are associated with a small, and often negative, response of labor input, see the rich literature starting from Galí (1999). For similar reasons, the alternative calibration also fails to generate the strong positive correlation of intermediate inputs with measured productivity. Third, the volatility of aggregate gross output falls to about the same level as that of aggregate value added, while in the data it is substantially larger. We conclude that the empirical performance of the model deteriorates in several dimensions if we try to explain the movements in productivity by technology shocks rather than factor utilization.

The second alternative that we consider is the case of flexible prices. The baseline calibration follows the New Keynesian literature and assumes a price rigidity parameter θ_i equal to 0.75 in all industries. Variation of the parameter value within the range usually assumed in the literature does not substantially change our conclusions. However, with perfectly flexible prices (case $\theta_i = 0$) the model outcomes become independent of nominal variables. Therefore, the aggregate demand shock generates zero fluctuations. To give the model a better chance to fit the data, we eliminate additional rigidities in the model by setting the labor supply elasticity to infinity, decreasing the capital adjustment costs, and eliminating the consumption habit and the measurement error on hours. Tables 2.12–2.15 present the results for the model with flexible prices. Industry technology shocks explain a bigger part of the aggregate fluctuations, because their propagation across the input-output network is stronger. Again, aggregate technology shocks are important. The performance of the model worsens along the same dimensions in the case of constant effort, and by a wider margin. The cross-industry correlations of productivity measures are too high, basically the same as those of value added and gross output. On the other hand, the cross-industry co-movement of hours is too low. The correlation of aggregate measured productivity with hours is too high, as hours now follow a typical positive RBC response to technology shocks. Moreover, in this case the model is not able to generate a sufficiently high response of aggregate hours. Aggregate gross output fluctuates much less than GDP, contrary to the data. The relative prices at the industry level still fluctuate substantially less than in the data, but now their correlation with industry measured productivity is also too negative.

The discussion of the alternative models highlights the importance of the industry-level information. The version of the model with no aggregate technology shocks is strongly supported by the low cross-industry correlation of measured productivity compared to output and hours, and by the fact that aggregate gross output fluctuates more than value added. The importance of the relative variance of gross output for identification of demand versus technology shocks deserves some further explanation. Technology shocks tend to make aggregate value added react more strongly, in percentage terms, than gross output: if the elasticity of substitution between labor and intermediate inputs is lower than unity, and the labor input response to a technology shock is not too strong, then intermediate inputs change proportionally less than gross output. Therefore, value added reacts proportionally more than gross output. This is not the case for demand shocks, which generate a comparatively stronger reaction of production factors. This mechanism explains why at the industry level, where technology shocks are dominating, gross output fluctuates less than value added. On the contrary, at the aggregate level, where demand shocks are dominant, gross output fluctuates more. We provide a simple analytical analysis in appendix 2.C.

A further industry-level statistic that speaks in favor of endogenous effort is the ratio of intermediate inputs per hour worked. The ratio is fluctuating in all three model variants because the relative price of labor and intermediate inputs is changing in response to the shocks. However, there is a further mechanism in the case of endogenous effort: cost minimization determines the ratio of intermediate inputs to *effective* labor input, given factor prices. With flexible effort, effective labor input fluctuates more than hours, making intermediate inputs per hour more volatile. This explains why the ratio of intermediate inputs per hour worked in the baseline model fluctuates more than in the two alternatives. Comparing tables 2.4, 2.9 and 2.13 shows that the average standard deviations of the ratio of intermediate inputs per hour at the industry level is 0.73 in the data, 0.52 in the baseline model, 0.30 in the model with constant effort, and 0.25 in the model with flexible prices, supporting the baseline calibration.

2.4.5 Changes in business cycle co-movement after 1984

Finally, we analyse the alternative calibration that tests the predictions of the model for the great moderation period. A growing branch of literature tries to explain the changes in the business cycle fluctuations in the U.S. in the mid-1980s, in particular the vanishing cyclicality of productivity. Molnárová (2020) shows that industry evidence provides important information for assessing the plausibility of the proposed explanations. A number of the mechanisms proposed in the literature imply that the changes in cyclicality should be equally visible at the industry and the aggregate level. This is not the case in the data. In this section, we investigate to what extent our model is able to explain the changes in the mid-1980s taking into account both aggregate and industry-level evidence.

The bottom panels of tables 2.3 - 2.5 show the data moments in the post-1984 period and simulation results for the alternative calibration. The comparison of the industry data moments (tables 2.4 - 2.5) for periods before and after 1984 shows that many of the business cycle statistics are remarkably stable between the two sub-samples. While the absolute size of the fluctuations is smaller in the post-1984 period, most of the relative volatilities and correlations do not change much. However, the comparison of the aggregate data moments between the periods pre- and post-1984 in table 2.3 shows that there are some important differences.

- The absolute size of the aggregate fluctuations is smaller in the post-1984 period.
- The correlation between aggregate measured productivity and hours decreased from 0.49 to -0.26, the correlation with output decreased from 0.85 to 0.47, the change for measured labor productivity being similarly striking. Other correlations reported in the table also decreased in the post 1984-period, although the differences are much smaller.
- Standard deviations of aggregate factor inputs, labor and intermediate inputs, increased relative to the standard deviation of value added.
- The ratio of intermediate inputs over hours, at the aggregate level became less correlated with output and productivity.

Several authors have suggested that the great moderation period after 1984 was characterised by a different composition of shocks, especially stressing the lower volatility of shocks to aggregate demand, or muted effects of these shocks on the economy, see e.g. Barnichon (2010) and Galí and Gambetti (2009). Therefore, we decrease the volatility of the aggregate demand shock in our model in line with the empirical evidence and test the model predictions for the cyclicality of measured productivity. We keep the rest of the parameters, including the variances of industry shocks, the same as in the baseline. We decrease the volatility of the aggregate demand shock σ_D by around 40% such that the model exactly replicates the moderate decrease in the correlation of output and measured hours observed in the data.

The bottom panels of tables 2.3 and 2.4 show the second moments of the model variables generated using this alternative calibration and compare them to the data in the post-1984 period. The single change in the calibration of our model generates a significant part of the vanishing cyclicality of labor productivity observed in the aggregate data. In the model, the correlation between aggregate measured TFP and hours decreases to 0.11, which corresponds to 50% of the observed change. The correlation between measured TFP and output decreases from 0.87 to 0.79, which corresponds to 19% of the observed change. At the same time, the correlation between measured TFP and value added at the industry level stayed on average virtually unchanged both in the data and in the model. The average correlation between the industry measured TFP and hours in the data decreased moderately from -0.02 to -0.23, while the model generates around 65% of the decrease, from -0.06 to -0.20.

To summarize, the alternative calibration of the model replicates the post-1984 decrease in the volatility of aggregate output and productivity, and it generates a significant part of the decrease in the procyclicality of measured aggregate productivity, without generating a counterfactual decrease in procyclicality of productivity at the industry level. Looking at a larger set of moments, however, there are several dimensions along which the alternative calibration is less successful. In particular, the correlation of aggregate measured productivity with output and intermediate inputs has decreased significantly more in the data than in the model.

2.5 Concluding remarks

In this paper, we have developed a highly disaggregated DSGE model with input-output linkages between industries. We use this framework to study the relative importance of technology and demand shocks, both at the aggregate and industry level. Our model supports the view that there are no aggregate technology shocks. We find that all the variation in observed productivity can be explained by two components: idiosyncratic technology shocks at the industry level and endogenous variations in factor utilization, driven by shocks to aggregate demand. Considering only aggregate empirical evidence, it would be difficult to distinguish between a model with endogenous effort and a model with aggregate technology shocks. However, we show that the model with endogenous effort matches the industry-level evidence much better than the model with aggregate technology shocks. There is small but highly important co-movement of measured productivity across industries, which points towards the presence of an aggregate component. The co-movement pattern is explained well in our model with endogenous fluctuations in effort, caused by the aggregate shocks to demand, while it is exaggerated in the model with aggregate technology shocks.

Our results support a Keynesian view of business cycles in the sense that aggregate demand shocks are the main driver of aggregate fluctuations. They explain 78 percent of the fluctuations in aggregate hours, with the remaining part being attributed to measurement errors. This is in line with recent evidence in Angeletos et al. (2020) and Andrle et al. (2017). Since we model the aggregate demand shock as a risk premium wedge affecting the inter-temporal substitution, we also see our results as consistent with Hall (2017), who shows that fluctuations in employment are primarily driven by changes in financial discount factors. Our estimates attach an important role to endogenous effort, in line with Fernald and Wang (2016), who find that the procyclicality of measured productivity is mostly due to endogenous factor utilization.

We have also explored to what extent our model can account for the change in the cyclicality of productivity after the mid-1980s. We find that a reduction in the variance of aggregate demand shocks, compatible with the great moderation narrative, explains a substantial part of the reduction in correlations between aggregate measured productivity and labor input. However, it explains only a small part of the change of some other moments, such as correlation between aggregate productivity and output. Clearly, there are other aspects of the changes in the great moderation period which our model does not take into account. While we cannot fully account for the change in the cyclical properties of productivity after 1984, our results support the view that the vanishing cyclicality of measured productivity should not be interpreted as a reduced role of technology shocks. In fact, technology shocks have never been a major driver in the procyclicality of measured productivity in the first place.

Our findings have potential implications for both monetary and fiscal policy. For monetary policy, the correct identification of productivity shocks is crucial for determining the output gap. Kiley (2013) shows that the estimated output gap in DSGE models is strongly affected by the estimated variations in measured aggregate technology. Thus, the correct identification of sources of the macroeconomic fluctuations, both real-time and ex post, is important for choosing the adequate reaction of monetary policy. Moreover, the response of monetary policy following an industry-specific shock might have stronger redistributive effects.

The recent literature has stressed the stabilization role of fiscal policy after shifts in aggregate demand. Government purchases of goods and services generate demand in the specific industries which spill over to the rest of the economy. Due to differences in the industry structure and input-output network, the effects of fiscal policies depend on the allocation of resources across industries. Understanding the transmission mechanisms in a disaggregated general equilibrium model can help identify those fiscal measures that are most effective in generating output and employment, see the discussion in chapter 3.

Appendix 2

2.A First order conditions and equilibrium

Optimal composition of labor input

For any given firm demand for labor input $\bar{l}$, households are free to choose how much effort e and hours h they supply such that $\bar{l} = eh$. In each period, the optimizing household chooses hours and effort supplied to industry i to minimize the disutility from working

$$\min_{h_i, e_i} g(h_i, e_i), \tag{2.37}$$

such that

$$h_i e_i = \bar{l}_i, \tag{2.38}$$

where function g is given in 2.10. The associated first order condition gives

$$e_i = \Lambda_i^{-\frac{1}{\sigma_e}} h_i^{\frac{\sigma_h}{\sigma_e}}. \tag{2.39}$$

Substituting into equation 2.11 we get

$$h_i = \Lambda_i^{\frac{1}{\sigma_e+\sigma_h}} l_i^{\frac{\sigma_e}{\sigma_e+\sigma_h}} \tag{2.40}$$

Substituting 2.39 into 2.10 we get

$$\begin{aligned} g(e_i, h_i) &= \kappa_0 h_i^{\frac{\sigma_e+\sigma_h}{\sigma_e}} &(2.41)\\ &= \kappa_0 \Lambda_i^{\frac{1}{\sigma_e}} l_i, &(2.42)\end{aligned}$$

where

$$\kappa_0 = \left(\frac{\sigma_e + \sigma_h}{\sigma_e \sigma_h}\right)^{\frac{\sigma_h+\sigma_e}{\sigma_h \sigma_e}}. \tag{2.43}$$

Function g is linear in effective labor input l_i, which implies that the household problem is convex (budget constraint is linear in l_i and household utility function is convex in g).

Household problem

Households maximize their objective function 2.4 with respect to the budget constraint 2.13, capital evolution equation 2.22, non-negativity constraints on K_t, $l_{i,t}$ and C_t and two no-Ponzi conditions corresponding to the two assets B_t, K_t. In a symmetric equilibrium, no household can borrow in bonds or hold negative capital. Thus, the no-Ponzi conditions are always satisfied. The problem of the household is convex and leads to an interior solution, thus the non-negativity constraints are always satisfied. We solve the reduced problem of maximizing 2.4 with respect to 2.13 and 2.22 by differentiating the Lagrangian:

$$\begin{aligned} C_t &: \lambda_t = U_C(C_t, N_t) &(2.44)\\ l_{i,t} &: -\lambda_t w_{i,t} = U_{l_i}(C_t, N_t) &(2.45)\\ B_t &: \lambda_t = \beta \, \mathrm{E}_t \left[\lambda_{t+1} r^B_{t+1}\right] &(2.46)\\ K_t &: \nu_t = \beta \, \mathrm{E}_t \left[\nu_{t+1}(1 - \delta + \phi(\iota_{t+1})) + \beta \lambda_{t+1}(r^k_{t+1} - P^X_{t+1}\iota_{t+1})\right] &(2.47)\\ \iota_t &: \lambda_t P^X_t = \nu_t \phi_\iota(\iota_t) &(2.48)\end{aligned}$$

where λ_t and ν_t are Lagrange multipliers corresponding to constraints (2.13) and (2.22), respectively. U_C and U_{l_i} denote the derivatives of household objective function w.r.t. the corresponding variables. Equations 2.44 and 2.45 together lead to the intratemporal condition

$$-w_{i,t} U_C(C_t, N_t) = U_{l_i}(C_t, N_t). \tag{2.49}$$

Equations 2.44 and 2.46 together yield the household Euler equation

$$U_C(C_t, N_t) = \beta \, \mathrm{E}_t \, D_t \frac{R_t}{\pi_{t+1}} U_C(C_{t+1}, N_{t+1}). \tag{2.50}$$

Using the standard definition of Tobin's Q (denoted Q^T), equation 2.48 can be rearranged as

$$\nu_t = P_t^X \frac{\lambda_t}{\phi_\iota(\iota_t)} = P_t^X \lambda_t Q_t^T \tag{2.51}$$

and plugged into equation 2.47 to obtain the optimal investment condition

$$Q_t^T = \mathrm{E}_t \, Q_{t,t+1} \pi_{t+1}^X \left[\frac{r_{t+1}^k}{P_{t+1}^X} - \iota_{t+1} + Q_{t+1}^T (1 - \delta + \phi(\iota_{t+1})) \right], \tag{2.52}$$

where

$$\pi_{t+1}^X = \frac{P_{t+1}^X}{P_t^X} \frac{P_{t+1}}{P_t} = \frac{P_{t+1}^X}{P_t^X} \pi_{t+1} \tag{2.53}$$

is the inflation in the nominal price of capital.

Firm problem

Given the firm prices, the demand for products of each firm is determined. Firm k in industry i faces the problem of optimal choice of production inputs, such that it can satisfy the demand.

$$\min_{k_{ki,t}, l_{ki,t}, m_{k,1..I,t}} \quad w_{i,t} l_{ki,t} + r_t^k k_{ki,t} + \sum_j p_{j,t} m_{k,ji,t} \tag{2.54}$$

such that

$$y_{ki,t}(p_{ki,t}) + \Phi_i = F^i(A_t, z_{i,t}, k_{ki,t}, l_{ki,t}, M_{ki,t}), \tag{2.55}$$

where F^i is the production function in industry i, $l_{ki,t}$, $k_{ki,t}$, $M_{ki,t}$ are firm-level input factors and $w_{i,t}$, $r_{i,t}^k$, $P_{i,t}^M$ are the corresponding prices.

Optimal behaviour of firms in industry i implies that the first order condition

$$\frac{m_{j_1,i}}{m_{j_2,i}} = \frac{\alpha_{j_1,i}}{\alpha_{j_2,i}} \left(\frac{p_{j_2}}{p_{j_1}} \right)^{\sigma_M} \tag{2.56}$$

holds for each j_1, j_2. The price index of intermediate goods used in industry i, $P_{i,t}^M$, follows from the production function of intermediate good M_i,

$$P_{i,t}^M = \left(\sum_{j=1}^I \alpha_{ji} {p_{j,t}}^{1-\sigma_M} \right)^{\frac{1}{1-\sigma_M}}. \tag{2.57}$$

Due to the constant returns to scale technology for M_i, the price index is the same for all firms in industry i, as they optimally choose the same composition of intermediate inputs.

Differentiating the Lagrangian w.r.t. $l_{ki,t}$, $k_{ki,t}$, $M_{ki,t}$ we obtain the standard conditions

$$\frac{w_{i,t}}{\lambda_{ki,t}} = \frac{\partial F^i}{\partial l_{ki,t}} \tag{2.58}$$

$$\frac{r_t^k}{\lambda_{ki,t}} = \frac{\partial F^i}{\partial k_{ki,t}} \tag{2.59}$$

$$\frac{P_{i,t}^M}{\lambda_{ki,t}} = \frac{\partial F^i}{\partial M_{ki,t}} \tag{2.60}$$

where $\lambda_{ki,t}$ is the Lagrange multiplier associated with condition 2.55. The first two conditions lead to

$$\frac{w_{i,t}}{r_t^k} = \frac{\partial F^i/\partial l_{ki,t}}{\partial F^i/\partial k_{ki,t}} \tag{2.61}$$

and the second two conditions give

$$\frac{w_{i,t}}{P_{i,t}^M} = \frac{\partial F^i/\partial l_{ki,t}}{\partial F^i/\partial M_{ki,t}}. \tag{2.62}$$

It is straightforward to derive the firm-level optimality condition

$$RMC_{i,t} = \frac{r_t^k}{\partial F^i/\partial k_{ki,t}}, \tag{2.63}$$

and analogous conditions for $l_{ki,t}, M_{ki,t}$, where real marginal costs are given as

$$RMC_{i,t} = \frac{1}{A_t z_{i,t}} \left(\mu_{i,K} {r_t^k}^{1-\sigma_y} + \mu_{i,L} {w_{i,t}}^{1-\sigma_y} + \mu_{i,M} {P_{i,t}^M}^{1-\sigma_y} \right)^{\frac{1}{1-\sigma_y}}. \tag{2.64}$$

Equation 2.63 implies that all firms operating in industry i choose inputs such that the partial derivatives $\partial F^i/\partial k_{ki,t}$ are the same across firms. Equations 2.61 to 2.63 thus hold at the industry level as well.

Apart from the fixed costs, the production technology is constant returns to scale, therefore real costs are linear in output.

$$Costs(y_{ki,t} + \Phi_i) = RMC_{i,t} \cdot (y_{ki,t} + \Phi_i). \tag{2.65}$$

Plugging the production function 2.15 into 2.63 and reorganizing, we get

$$k_{ki,t} = (A_t z_{it})^{\sigma_y - 1} \mu_{i,K} \left(\frac{r_{i,t}^k}{RMC_{i,t}} \right)^{-\sigma_y} (y_{ki,t} + \Phi_i)., \tag{2.66}$$

and corresponding equations for labor and intermediate inputs.

Industry production

Industry demand for labor follows from the market clearing condition

$$
\begin{aligned}
l_{i,t} &= \int_0^1 l_{ki,t}\, dk && (2.67)\\
&= \Theta_{i,t} \int_0^1 y_{ki,t} + \Phi_i \, dk && (2.68)\\
&= \Theta_{i,t}\Phi_i + \Theta_{i,t} y_{i,t} \int_0^1 \left(\frac{p_{ki,t}}{p_{i,t}}\right)^{-\sigma_I} dk, && (2.69)
\end{aligned}
$$

where

$$
\Theta_{i,t} = (A_t z_{it})^{\sigma_y - 1} \mu_{i,L} \left(\frac{w_{i,t}}{RMC_{i,t}}\right)^{-\sigma_y} \tag{2.70}
$$

depends on industry-level prices and parameters only. Expression

$$
Disp_{i,t} = \int_0^1 \left(\frac{p_{ki,t}}{p_{i,t}}\right)^{-\sigma_I} dk \tag{2.71}
$$

is the price dispersion term. A standard result from the New Keynesian literature shows that the dispersion term has only second-order effects around the zero-inflation steady state. It follows that

$$
l_{i,t} \approxeq (A_t z_{i,t})^{\sigma_y - 1} \mu_{i,L} \left(\frac{w_{i,t}}{RMC_{i,t}}\right)^{-\sigma_y} (y_{i,t} + \Phi_i), \tag{2.72}
$$

up to the first order approximation.

Next, we derive the total demand for a particular good i and show it is independent of firm-specific variables up to the first order approximation. We start with determining the demand for i as intermediate input. In line with 2.72, demand for intermediate good aggregate $M_{j,t}$ in industry j is

$$
M_{j,t} \approxeq (A_t z_{j,t})^{\sigma_y - 1} \mu_{j,M} \left(\frac{P^M_{j,t}}{RMC_{j,t}}\right)^{-\sigma_y} (y_{j,t} + \Phi_j). \tag{2.73}
$$

An optimizing firm k in sector j chooses intermediate input from sector i according to

$$
m_{k,ij,t} = \alpha_{ij} \left(\frac{p_{i,t}}{P^M_{j,t}}\right)^{-\sigma_M} M_{kj,t} \tag{2.74}
$$

Total intermediate input i as an input into industry j production can be expressed as

$$
\begin{aligned}
m_{ij,t} &= \int_0^1 m_{k,ij,t}\, dk && (2.75)\\
&= \alpha_{ij} \left(\frac{p_{i,t}}{P^M_{j,t}}\right)^{-\sigma_M} \int_0^1 M_{kj,t}\, dk && (2.76)\\
&\approxeq \Gamma_{ij,t}(y_{j,t} + \Phi_j), && (2.77)
\end{aligned}
$$

where the parameter $\Gamma_{ij,t}$ is independent of the firm's actions,

$$\Gamma_{ij,t} = \alpha_{ij}\mu_{j,M}(A_t z_{j,t})^{\sigma_y - 1}\left(\frac{p_{i,t}}{P^M_{j,t}}\right)^{-\sigma_M}\left(\frac{P^M_{j,t}}{RMC_{j,t}}\right)^{-\sigma_y}. \tag{2.78}$$

Thus, the total demand for industry i's good can be expressed as

$$\begin{aligned} y_{i,t} &= c_{i,t} + x_{i,t} + \sum_j m_{ij,t} && (2.79)\\ &\approxeq v_{i,t} p_{i,t}{}^{-\sigma_C} C_t + \xi_i \left(\frac{p_{i,t}}{P^X_t}\right)^{-\sigma_X} X_t + \sum_j \Gamma_{ij,t}(y_{j,t} + \Phi_j). && (2.80) \end{aligned}$$

Price setting

The period $t+s$ demand for the product of a firm that has last updated its price in period t can be expressed using 2.2 as

$$y_{ki,t+s|t} = \left(\frac{p^{NOM}_{ki,t}}{p^{NOM}_{i,t+s}}\right)^{-\sigma_I} y_{i,t+s} \tag{2.81}$$

where superscript NOM denotes the nominal prices. Equation 2.80 shows that $y_{i,t+s}$ does not depend on the individual firm-level variables.

In nominal terms, the price-setting problem of each firm is to maximize 2.17:

$$\max_{p_{ki,t}, y_{ki,t}, .., y_{ki,\infty}} \mathrm{E}_t \sum_{s=0}^{\infty} \theta_i{}^s Q_{t,t+s}\left[y_{ki,t+s|t}(p^{NOM}_{ki,t} - NMC_{i,t+s}) - \Phi_i NMC_{i,t+s}\right]. \tag{2.82}$$

with respect to 2.81. Nominal marginal costs NMC are defined as

$$NMC_{i,t} = P_t \cdot RMC_{i,t} \tag{2.83}$$

Differentiating the Lagrangian we obtain

$$\begin{aligned} p^N_{ki,t} &: \mathrm{E}_t \sum_{s=0}^{\infty} \theta_i{}^s Q_{t,t+s} y_{ki,t+s|t} - \sum_{s=0}^{\infty} \varrho_{t+s}\sigma_I \frac{(p^{NOM}_{ki,t})^{-\sigma_I - 1}}{(p^N_{i,t+s})^{-\sigma_I}} y_{i,t+s} = 0 && (2.84)\\ y_{ki,t+s|t} &: \theta_i{}^s Q_{t,t+s}[p^{NOM}_{ki,t} - NMC_{i,t+s}] = -\varrho_{t+s} && (2.85) \end{aligned}$$

ϱ_t denoting the Lagrange multiplier corresponding to the constraint 2.81 at time t. Substituting 2.85 into 2.84 we get

$$\mathrm{E}_t \sum_{s=0}^{\infty} \theta_i{}^s Q_{t,t+s}\left[y_{ki,t+s|t} - [p^{NOM}_{ki,t} - NMC_{i,t+s}]\sigma_I \frac{(p^N_{ki,t})^{-\sigma_I - 1}}{(p^N_{i,t+s})^{-\sigma_I}} y_{i,t+s}\right] = 0 \tag{2.86}$$

$$\mathrm{E}_t \sum_{s=0}^{\infty} \theta_i{}^s Q_{t,t+s} y_{ki,t+s|t}\left[p^{NOM}_{ki,t} - \frac{\sigma_I}{\sigma_I - 1} NMC_{i,t+s}\right] = 0 \tag{2.87}$$

In a symmetric equilibrium, all firms within an industry i that set their prices in period t choose the same optimal price $p_{ki,t}^{NOM} = p_{i,t}^{NOM*}$.

Aggregation

$$H_t = \sum_{i=1}^{I} h_{i,t} \tag{2.88}$$

$$H_t^m = \sum_{i=1}^{I} h_{i,t}^m \tag{2.89}$$

$$K_{t-1} = \sum_{i=1}^{I} k_{i,t} \tag{2.90}$$

$$P_t^Y Y_t = \sum_{i=1}^{I} p_{i,t} y_{i,t} \tag{2.91}$$

$$P_t^{\dot{M}} \dot{M}_t = \sum_{i=1}^{I} P_{i,t}^M M_{i,t} \tag{2.92}$$

Equilibrium

The equilibrium of the generalized model is determined by the following set of $14+15 \times I$ equations:

- $2+2I$ exogenous shock processes 2.25 - 2.29
- $2+2I$ FOCs from household problem 2.39, 2.49, 2.50, 2.52
- $3I$ FOCs from firm cost-optimisation 2.61 - 2.63
- I firm production functions 2.15
- I FOCs from firm price setting problem 2.87
- I industry price evolution equations 2.16
- I optimal demand for industry good in final consumption conditions 2.7
- I optimal demand for industry good in investment creation 2.19
- I equations for price indexes of industry intermediate inputs 2.57
- I equations for effective labor input 2.11
- I good market clearing conditions 2.24
- 1 Taylor rule 2.23
- 1 capital evolution equation 2.22
- 1 equation defining aggregate investment 2.21
- 1 relative price of investment good 2.20
- 1 CPI normalization
- 5 aggregating equations for Y, K, H^m, H, $\dot{M}$ 2.88 - 2.92

The equations jointly solve for the following $14 + 15 \times I$ variables:

- $2+2I$ exogenous shocks A, D, z_i, v_i

- 12 aggregate variables Y, K, H^m, H, M, X, C, r, r^k, ι, π, P^X
- $13I$ industry variables y, k, l, h, M, p, P^M, c, e, x, w, RMC, p^*

Moreover, in the numerical solution and in the analysis of model results we use the following auxiliary variables:

- 10 aggregate variables VA, π^X, λ, Q, Q^T, T, II/H, LP, $TFPm$, TFP
- $8I$ industry variables va, $prof$, wh, ii/h, lp, tfp, SA, SB

Each of the auxiliary variables is defined by a corresponding equation. In total, our numerical programme features $24 + 23 \times I = 1795$ variables.

2.B Data and calibration

2.B.1 Additional information about the data and construction of moments

The list of the industries, as well as the details describing the construction of data series and moments coincide with appendix 1.A in chapter 1 of this thesis. The only difference is that in this paper we do not winsorize the standard deviation of value added and measured productivity for the two extremely volatile industries.

2.B.2 Industry-specific weight parameters

The investment good composition weights ξ_i are set to match the cost shares of investment from the 1992 BEA capital-flow table. As the model only features one type of investment, we use the average composition across all industries to calibrate weights ξ_i. BEA capital-flow tables use classification of input commodities that differs from the industry classification in Jorgenson data set, but BEA provides the mapping of commodities into SIC categories. Using this information, the data sets can be almost perfectly mapped into each other. The only exceptions are two BEA commodities *transportation* and *retail trade*, which we can not be match with more detailed categories in the Jorgenson database. We split the goods flow equally between six transportation-related industries (*railroad transportation, local passenger transit, trucking and warehousing, water transport, air transport, transportation services and pipelines*), resp. between two retail industries (*retail trade excluding motor vehicles, retail trade of motor vehicles*). Importantly, the flows of the two problematic commodities into capital formation are small, thus the potential error we create by assuming the equal cost shares is limited.

The consumption composition weights ν_i are set to match the cost shares of consumption from the 1992 BEA input-use table. We include the categories personal consumption expenditures, private residential fixed investment and exports of goods and services. We use six digit level of SIC classification table to map the flows to Jorgenson database industries. Similar problem to capital flow tables emerges for SIC industry *retail trade*, which can not be split into *retail trade excluding motor vehicles* and *retail trade of motor vehicles*. Although the model does not explicitly account for exports and imports, we try to calibrate the industry structure as close to reality as possible. We include exports of goods and services in order to preserve the realistic output shares of the industries. On the other hand, this limits the possibility to interpret ν_i as weights of consumption in the household utility.

2.B.3 Elasticities σ_y, σ_M

In our model, σ_y is both the firm- and industry-level elasticity of substitution between production factors (k_i, l_i, M_i) in producing output y_i. Optimizing firms choose inputs such that:

$$\frac{k_i}{l_i} = \frac{\mu_{i,K}}{\mu_{i,L}} \left(\frac{w_i}{r^k}\right)^{\sigma_y}, \tag{2.93}$$

where corresponding FOCs also hold for comparing capital and labor input with intermediate inputs aggregate M_i and its price P_i^M. Constant parameters $\mu_{i,K/L/M}$ are pinned down by the average factor use by industry. Therefore, in the model holds that

$$\ln\left(\frac{k_i}{l_i}\right) = \sigma_y \ln\left(\frac{w_i}{r^k}\right) + \ln\left(\frac{\mu_{i,K}}{\mu_{i,L}}\right), \tag{2.94}$$

where the last term is constant. Thus, we can obtain σ_y by regressing the simulated data series up to a first order approximation.

Multiplying 2.93 by prices, we get

$$\begin{aligned} \ln\left(\frac{k_i r^k}{l_i w_i}\right) &= \sigma_y \ln\left(\frac{w_i}{r^k}\right) + \ln\left(\frac{r^k}{w_i}\right) + const. && (2.95)\\ &= (\sigma_y - 1)\ln\left(\frac{w_i}{r^k}\right) + const. && (2.96) \end{aligned}$$

where $\sigma_y > 0$, $\eta_y = \sigma_y - 1 > -1$. Taking differences we get

$$d\ln\left(\frac{k_i r^k}{l_i w_i}\right) = \eta_y d\ln\left(\frac{w_i}{r^k}\right) \tag{2.97}$$

which is the specification we use to compare the model elasticity to the data.

Further, σ_M is the elasticity of substitution between intermediate inputs (m_{ji}) in constructing intermediate input M_i. Optimal behaviour in industry i implies the FOC

$$\frac{m_{j_1,i}}{m_{j_2,i}} = \frac{\alpha_{j_1,i}}{\alpha_{j_2,i}} \left(\frac{p_{j_2}}{p_{j_1}}\right)^{\sigma_M} \tag{2.98}$$

holds for each j_1, j_2. We can follow the same procedure and obtain the model version of the regression equation for σ_M.

We use equation 2.97 as identifying assumption and regress the left-hand side on the right-hand side. We compute the regression coefficient as

$$\hat{\eta}_y = corr\left[d\ln\left(\frac{k_i r^k}{l_i w_i}\right), d\ln\left(\frac{w_i}{r^k}\right)\right] \frac{SD\left(d\ln\left(\frac{k_i r^k}{l_i w_i}\right)\right)}{SD\left(d\ln\left(\frac{w_i}{r^k}\right)\right)}. \tag{2.99}$$

The large number of industry-level series gives 77×3 equations to estimate σ_y and $77 \times \frac{76 \cdot 75}{2}$

equations to estimate σ_M. We use the average across all industry pairs to pin down σ_M. For σ_y we use the average across 77 labor/intermediate inputs coefficients, because the capital accounts are the least reliable of the three production factors. Before computing the simple average elasticity across industries we winsorize all the elasticities smaller than -1.

Using the industry-level information about the labor input and intermediate inputs we obtain $\hat{\sigma}_y = 0.39$. Using other combinations of factors leads to similar estimates, slightly closer to zero. For the estimation of σ_M, using all pairs of industry-to-industry flows, we obtain that $\hat{\sigma}_M = 0.75$. The distribution of the pair-specific $\hat{\sigma}_M$ has a number of strong outliers, therefore winsorizing has a relatively big effect in this case.

2.B.4 Elasticity σ_U

The combination of σ_e and the elasticity of total labor input σ_U determines the wage elasticity of hours comparable to the standard Frisch elasticity in the aggregate macroeconomic models. The intratemporal FOC 2.49 implies that

$$-w^h_{i,t}/C_t = U_{h_i}(C_t, N_t) = \kappa N_t^{\frac{1}{\sigma_U} - \frac{1}{\sigma_N}} l_{i,t}^{\frac{1}{\sigma_N}} h_{i,t}^{\frac{\sigma_h}{\sigma_e}}, \tag{2.100}$$

where w^h is wage per hour, κ is a constant, $\sigma_h = 1$ w.l.o.g., and we can plug in hours and effective labor from equations 2.40 and 2.41. It is straightforward to derive the Frisch elasticity as the relationship between a change (simultaneous, in all industries) in hourly wages and hours worked. The Frisch elasticity can be expressed as $\cdot \frac{\sigma_U \sigma_e}{\sigma_e + \sigma_U + 1}$. The parameter σ_U is calibrated such that the implied Frisch elasticity is around 0.5, within the range considered in the DSGE literature.

2.C Gross output versus value added fluctuations

Technology and demand shocks have different effects on the ratio of gross output versus net output fluctuations. This can be illustrated most easily in the case of a Leontieff technology. Assume the aggregate production function

$$Y = A \min\{L, M\}, \qquad A > 1 \tag{2.101}$$

for gross output Y with the factors labor L and intermediate inputs M. Value added is then given by $VA = Y - M$. Cost minimization implies $L = M$ and therefore

$$VA = (A-1)L. \tag{2.102}$$

Variations in A (technology shocks), keeping labor input L constant, then imply

$$\frac{dY/dA}{Y} \Big/ \frac{dVA/dA}{VA} = \frac{L}{L}\frac{(A-1)L}{AL} = \frac{A-1}{A} < 1, \tag{2.103}$$

which means that gross output fluctuates proportionally less than value added. In contrast, variations in L for constant A, as they arise from demand shocks, lead to

$$\frac{dY/dA}{Y} \Bigg/ \frac{dVA/dA}{VA} = \frac{A}{A-1}\frac{(A-1)L}{AL} = 1, \tag{2.104}$$

so that gross and net output fluctuate equally strongly. This toy model does not make gross output fluctuate more than value added, but it shows that demand fluctuations generate fluctuations in gross output which are bigger than technology shocks.

2.D Additional model results

2.D.1 Alternative calibration: constant effort

Aggregate variables: second moments									
	Standard dev. relative to output			Correlations with output			Correlations w. measured TFP		
	Data	(SE)	Model	Data	(SE)	Model	Data	(SE)	Model
Constant effort									
Value added	1.00	(0.00)	1.00	1.00	(0.00)	1.00	0.85	(0.06)	0.82
Gross output	1.17	(0.05)	1.03	0.98	(0.00)	0.93	0.80	(0.08)	0.61
Measured TFP	0.62	(0.03)	0.76	0.85	(0.06)	0.82	1.00	(0.00)	1.00
Hours	0.83	(0.07)	0.83	0.86	(0.03)	0.60	0.49	(0.12)	0.07
Intermediate inputs	1.37	(0.09)	1.19	0.95	(0.01)	0.76	0.74	(0.08)	0.35
Inflation	0.93	(0.08)	0.68	0.14	(0.17)	0.52	-0.11	(0.24)	0.05
Labor productivity	0.51	(0.05)	0.82	0.56	(0.13)	0.60	0.89	(0.03)	0.94
Int. inputs per hour	0.77	(0.05)	0.63	0.76	(0.03)	0.65	0.80	(0.03)	0.58
Investment	-	-	2.68	-	-	0.93	-	-	0.68
Consumption	-	-	0.58	-	-	0.81	-	-	0.81
True TFP	-	-	0.63	-	-	0.72	-	-	0.93

Table 2.8: Comparison of selected second moments in the model and in the data, aggregate variabes. Calibration with constant effort contrasted to the data in the pre-1984 period.

Industry variables: averages across second moments									
	Standard dev. relative to output			Correlations with output			Correlations w measured TFP		
	Data	(SE)	Model	Data	(SE)	Model	Data	(SE)	Model
Constant effort									
Value added	1.00	(0.06)	1.00	1.00	(0.00)	1.00	0.78	(0.01)	0.69
Gross output	0.71	(0.00)	0.79	0.84	(0.01)	0.88	0.57	(0.01)	0.39
Measured TFP	0.36	(0.01)	0.35	0.78	(0.01)	0.69	1.00	(0.00)	1.00
Hours	0.56	(0.02)	0.77	0.38	(0.02)	0.45	-0.02	(0.03)	-0.23
Intermediate inputs	0.83	(0.01)	0.81	0.35	(0.04)	0.56	0.14	(0.02)	-0.04
Prices	0.66	(0.03)	0.21	-0.33	(0.01)	-0.32	-0.43	(0.02)	-0.54
Input prices	0.33	(0.04)	0.10	-0.13	(0.02)	-0.15	-0.16	(0.02)	-0.23
Labor productivity	0.95	(0.04)	0.82	0.72	(0.01)	0.61	0.84	(0.01)	0.96
Int. inputs per hour	0.73	(0.02)	0.30	0.17	(0.04)	0.29	0.22	(0.04)	0.41
True TFP	-	-	0.32	-	-	0.55	-	-	0.91

Table 2.9: Comparison of selected second moments in the model and in the data, industry variables. Calibration with constant effort contrasted to the data in the pre-1984 period. Reported numbers are weighted (by industry output) averages across industry moments.

Cross-Industry Correlations			
Constant effort	Data	(SE)	Model
Value added	0.14	(0.009)	0.15
Gross output	0.22	(0.015)	0.24
Measured TFP	0.05	(0.008)	0.13
Hours	0.20	(0.011)	0.15
Intermediate inputs	0.19	(0.035)	0.25
Output price	0.07	(0.015)	0.01
Input price	0.15	(0.017)	0.21
Labor productivity	0.02	(0.006)	0.13
True TFP	-	-	0.12

Table 2.10: Average cross-industry pairwise correlations. Calibration with constant effort contrasted to the data in the pre-1984 period.

Variance Decomposition: constant effort					
Shocks	Aggregate		Industry		Measurement
	technology	demand	technology	demand	error
Industry variables					
Value added	0.09	0.07	0.22	0.61	0.00
Gross output	0.06	0.16	0.04	0.73	0.00
Measured TFP	0.11	0.01	0.78	0.03	0.07
Hours	0.02	0.13	0.12	0.60	0.12
Intermediate inputs	0.03	0.22	0.12	0.61	0.00
Output price	0.02	0.03	0.94	0.01	0.00
Labor productivity	0.12	0.01	0.70	0.06	0.10
Investment good production	0.31	0.61	0.10	0.00	0.00
Consumption	0.00	0.00	0.00	0.99	0.00
True TFP	0.10	0.00	0.90	0.00	0.00
Aggregate variables					
Value added	0.52	0.39	0.10	0.00	0.00
Gross output	0.24	0.69	0.06	0.02	0.00
Measured TFP	0.75	0.03	0.13	0.00	0.08
Hours	0.02	0.78	0.02	0.00	0.16
Intermediate inputs	0.07	0.84	0.03	0.06	0.00
Inflation	0.02	0.96	0.01	0.01	0.00
Labor productivity	0.68	0.02	0.12	0.00	0.16
Investment	0.30	0.61	0.09	0.00	0.00
Consumption	0.76	0.08	0.13	0.02	0.00
True TFP	0.84	0.00	0.14	0.00	0.00

Table 2.11: Variance decomposition of selected model variables. Calibration with constant effort.

2.D.2 Alternative calibration: Flexible RBC model

Aggregate variables: second moments									
	Standard dev. relative to output			Correlations with output			Correlations w. measured TFP		
	Data	(SE)	Model	Data	(SE)	Model	Data	(SE)	Model
Flexible prices									
Value added	1.00	(0.00)	1.00	1.00	(0.00)	1.00	0.85	(0.06)	0.96
Gross output	1.17	(0.05)	0.80	0.98	(0.00)	0.99	0.80	(0.08)	0.96
Measured TFP	0.62	(0.03)	0.69	0.85	(0.06)	0.96	1.00	(0.00)	1.00
Hours	0.83	(0.07)	0.51	0.86	(0.03)	0.81	0.49	(0.12)	0.65
Intermediate inputs	1.37	(0.09)	0.60	0.95	(0.01)	0.95	0.74	(0.08)	0.92
Inflation	0.93	(0.08)	1571.35	0.14	(0.17)	-0.01	-0.11	(0.24)	-0.01
Labor productivity	0.51	(0.05)	0.66	0.56	(0.13)	0.89	0.89	(0.03)	0.96
Int. inputs per hour	0.77	(0.05)	0.38	0.76	(0.03)	0.42	0.80	(0.03)	0.58
Investment	-	-	3.09	-	-	0.91	-	-	0.86
Consumption	-	-	0.57	-	-	0.63	-	-	0.65
True TFP	-	-	0.53	-	-	0.98	-	-	0.97

Table 2.12: Comparison of selected second moments in the model and in the data, aggregate variabes. Calibration with flexible prices contrasted to the data in the pre-1984 period.

Industry variables: averages across second moments									
	Standard dev. relative to output			Correlations with output			Correlations w measured TFP		
	Data	(SE)	Model	Data	(SE)	Model	Data	(SE)	Model
Flexible prices									
Value added	1.00	(0.06)	1.00	1.00	(0.00)	1.00	0.78	(0.01)	0.78
Gross output	0.71	(0.00)	0.67	0.84	(0.01)	0.95	0.57	(0.01)	0.62
Measured TFP	0.36	(0.01)	0.34	0.78	(0.01)	0.78	1.00	(0.00)	1.00
Hours	0.56	(0.02)	0.57	0.38	(0.02)	0.46	-0.02	(0.03)	-0.07
Intermediate inputs	0.83	(0.01)	0.56	0.35	(0.04)	0.63	0.14	(0.02)	0.18
Prices	0.66	(0.03)	0.34	-0.33	(0.01)	-0.45	-0.43	(0.02)	-0.65
Input prices	0.33	(0.04)	0.16	-0.13	(0.02)	-0.21	-0.16	(0.02)	-0.29
Labor productivity	0.95	(0.04)	0.84	0.72	(0.01)	0.76	0.84	(0.01)	0.97
Int. inputs per hour	0.73	(0.02)	0.25	0.17	(0.04)	0.25	0.22	(0.04)	0.45
True TFP	-	-	0.30	-	-	0.69	-	-	0.93

Table 2.13: Comparison of selected second moments in the model and in the data, industry variables. Calibration with flexible prices contrasted to the data in the pre-1984 period. Reported numbers are weighted (by industry output) averages across industry moments.

Cross-Industry Correlations			
Flexible prices	Data	(SE)	Model
Value added	0.14	(0.009)	0.19
Gross output	0.22	(0.015)	0.20
Measured TFP	0.05	(0.008)	0.18
Hours	0.20	(0.011)	0.09
Intermediate inputs	0.19	(0.035)	0.13
Output price	0.07	(0.015)	0.01
Input price	0.15	(0.017)	0.20
Labor productivity	0.02	(0.006)	0.16
True TFP	-	-	0.17

Table 2.14: Average cross-industry pairwise correlations. Calibration with flexible prices (RBC benchmark) contrasted to the data in the pre-1984 period.

Variance Decomposition: flexible prices					
Shocks	Aggregate		Industry		Measurement
	technology	demand	technology	demand	error
Industry variables					
Value added	0.17	0.00	0.50	0.33	0.00
Gross output	0.19	0.00	0.23	0.57	0.00
Measured TFP	0.13	0.00	0.80	0.02	0.05
Hours	0.08	0.00	0.15	0.61	0.15
Intermediate inputs	0.15	0.00	0.15	0.69	0.00
Output price	0.03	0.00	0.96	0.01	0.00
Input price	0.03	0.00	0.96	0.01	0.00
Labor productivity	0.12	0.00	0.78	0.03	0.07
Investment good production	0.46	0.00	0.53	0.00	0.00
Consumption	0.00	0.00	0.00	1.00	0.00
True TFP	0.10	0.00	0.89	0.00	0.00
Aggregate variables					
Value added	0.66	0.00	0.34	0.00	0.00
Gross output	0.64	0.00	0.34	0.01	0.00
Measured TFP	0.72	0.00	0.22	0.00	0.05
Hours	0.33	0.00	0.46	0.00	0.22
Intermediate inputs	0.57	0.00	0.33	0.08	0.00
Inflation	0.00	1.00	0.00	0.00	0.00
Labor productivity	0.66	0.00	0.19	0.00	0.13
Int. inputs per hour	0.25	0.00	0.12	0.22	0.40
Investment	0.44	0.00	0.56	0.00	0.00
Consumption	0.66	0.00	0.30	0.02	0.00
True TFP	0.79	0.00	0.21	0.00	0.00

Table 2.15: Variance decomposition of selected model variables. Calibration with flexible prices contrasted to the data in the pre-1984 period.

2.D.3 Additional robustness checks

In all robustness exercises, the variance of aggregate technology shock is zero. All alternative model calibrations deliver qualitatively similar results, with the exception of the version with zero measurement errors, see tables 2.17 and 2.16. Omitting the measurement errors increases the aggregate correlations between aggregate variables, but does not change the main results.

Robustness checks: industry variables								
	baseline	heter. θ_i	$\kappa = 10$	$\sigma_U = 3$	$\sigma_e = 3$	$\sigma_N = 2$	$\sigma_M = 0.3$	measure. error = 0
St. dev. relatiove to value added								
Value added	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Gross output	0.84	0.76	0.84	0.83	0.83	0.85	0.85	0.85
Measured TFP	0.38	0.35	0.40	0.36	0.37	0.39	0.39	0.39
Hours	0.60	0.51	0.61	0.59	0.65	0.58	0.62	0.52
Intermediate inputs	0.92	0.77	0.94	0.87	0.89	0.96	0.96	0.95
Prices	0.25	0.46	0.27	0.24	0.24	0.28	0.27	0.27
Input prices	0.11	0.21	0.12	0.10	0.11	0.12	0.12	0.12
Labor productivity	0.86	0.89	0.89	0.83	0.84	0.89	0.88	0.84
Int. inputs/hour	0.52	0.43	0.54	0.46	0.43	0.57	0.53	0.44
True TFP	0.36	0.32	0.38	0.34	0.35	0.37	0.38	0.38
Correlation with measured TFP								
Value added	0.81	0.82	0.81	0.81	0.77	0.81	0.80	0.86
Gross output	0.55	0.58	0.54	0.57	0.49	0.55	0.51	0.57
Measured TFP	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Hours	-0.06	-0.06	-0.09	-0.03	-0.11	-0.07	-0.10	0.11
Intermediate inputs	0.18	0.14	0.16	0.18	0.10	0.17	0.15	0.17
Prices	-0.54	-0.60	-0.54	-0.52	-0.56	-0.50	-0.53	-0.60
Input prices	-0.21	-0.27	-0.21	-0.20	-0.20	-0.19	-0.20	-0.24
Labor productivity	0.94	0.97	0.93	0.94	0.94	0.94	0.93	0.94
Int. inputs/hour	0.38	0.36	0.36	0.38	0.35	0.35	0.36	0.25
True TFP	0.73	0.76	0.75	0.73	0.82	0.74	0.73	0.79
Cross-industry correlations								
Value added	0.13	0.08	0.14	0.13	0.12	0.13	0.14	0.14
Gross output	0.30	0.16	0.33	0.27	0.28	0.30	0.30	0.33
Measured TFP	0.07	0.04	0.07	0.07	0.06	0.07	0.07	0.07
Hours	0.20	0.13	0.20	0.20	0.18	0.21	0.18	0.24
Intermediate inputs	0.36	0.21	0.39	0.31	0.33	0.35	0.34	0.39
Prices	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Input prices	0.21	0.13	0.22	0.22	0.23	0.22	0.21	0.21
Labor productivity	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.03
Int. inputs/hour	0.40	0.28	0.44	0.30	0.39	0.35	0.40	0.58
True TFP	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00

Table 2.16: Robustness checks: comparison of moments across various model calibrations. Industry variables (weighted average across industries).Heter. θ_i: heterogeneous price rigidity parameters across industries as estimated in Bouakez et al. (2014). Measure. error = 0: model version without measurement error shock.

Robustness checks: aggregate variables								
	baseline	heter. θ_i	$\kappa = 10$	$\sigma_U = 3$	$\sigma_e = 3$	$\sigma_N = 2$	$\sigma_M = 0.3$	measure. error = 0
St. dev. relatiove to value added								
Value added	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Gross output	1.32	1.24	1.34	1.21	1.27	1.31	1.31	1.31
Measured TFP	0.59	0.60	0.61	0.58	0.59	0.60	0.60	0.54
Hours	0.81	0.76	0.80	0.81	0.87	0.80	0.80	0.72
Intermediate inputs	1.68	1.53	1.72	1.46	1.60	1.67	1.66	1.67
Inflation	1.01	2.85	1.35	0.81	0.96	1.01	1.01	1.01
Labor productivity	0.54	0.60	0.56	0.53	0.58	0.55	0.55	0.39
Int. inputs/hour	1.04	0.96	1.09	0.84	0.93	1.04	1.03	0.95
Investment	3.29	4.07	2.88	3.24	3.20	3.25	3.27	3.28
Consumption	0.35	0.52	0.44	0.36	0.40	0.36	0.35	0.34
True TFP	0.27	0.31	0.29	0.26	0.35	0.27	0.28	0.26
Correlation with measured TFP								
Value added	0.87	0.85	0.87	0.88	0.83	0.88	0.88	0.96
Gross output	0.82	0.79	0.81	0.83	0.73	0.82	0.82	0.90
Measured TFP	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Hours	0.49	0.41	0.47	0.51	0.37	0.48	0.48	0.83
Intermediate inputs	0.77	0.72	0.76	0.78	0.65	0.77	0.77	0.85
Inflation	0.72	0.45	0.72	0.72	0.56	0.72	0.71	0.80
Labor productivity	0.88	0.89	0.89	0.88	0.87	0.89	0.89	0.91
Int. inputs/hour	0.87	0.82	0.86	0.86	0.77	0.87	0.86	0.86
Investment	0.83	0.78	0.83	0.84	0.76	0.83	0.83	0.92
Consumption	0.64	0.07	0.78	0.65	0.68	0.65	0.64	0.71
True TFP	0.40	0.51	0.44	0.43	0.61	0.42	0.43	0.45

Table 2.17: Robustness checks: comparison of moments across various model calibrations. Aggregate variables. Heter. θ_i: heterogeneous price rigidity parameters across industries as estimated in Bouakez et al. (2014). Measure. error = 0: model version without measurement error shock.

3 Industry differences in government spending multipliers in New Keynesian small open economy models

This chapter is joint work with Sebastian Koch.

3.1 Introduction

How big are government spending multipliers? After decades of empirical and theoretical research, the literature is providing us with a wide range of estimates and a long list of factors that influence the size of the multipliers, see e.g. Ramey (2019) for a recent review. However, policy makers trying to optimally allocate resources may find such information still vague and inconclusive. One of the reasons for this situation is that, even though the policy makers are usually interested in the aggregate macroeconomic outcomes, there is nothing like one universal value or *the* multiplier.

In this paper, we study the heterogeneity of government spending multipliers along a very natural dimension - across industries. We focus on multipliers in a small open economy, which we calibrate to resemble Austria. We show that a disaggregated New Keynesian model of small open economy predicts a very high heterogeneity across multipliers for government spending in each of the 74 individual industries. For example, in the case of a permanent increase in government consumption, the one-year ex-ante output multipliers vary from 0.75 to negative values depending on the industry. For government investment, the multipliers also vary depending on the type of capital: investment into machinery and transport equipment generates smaller short-run multipliers compared to other assets. Especially in the case of temporary spending shocks, government consumption in a number of service industries generates higher short-run multipliers than government investment.[1]

As the second contribution of the paper, we identify which industry characteristics drive the differences in spending multipliers. We show that the major sources of heterogeneity across multipliers are (1) differences in import shares across industries, (2) production factor shares (especially labor share and intermediate input share) and (3) asymmetry of the input-output network (different extent to which industry goods are used as intermediate inputs). The relative importance of these factors differs depending on the type of multiplier, considered time horizon, and persistence of the policy shock. However, industry import share is the most important

[1] A modified version of the model presented in this paper has been used in the applied project of the Institute for Advanced Studies (IHS Vienna) *IHS model for impact-oriented evaluation of public policies.* Thus, parts of the model description closely resemble the (unpublished) technical documentation, see Koch et al. (2019). The most important differences between the two models include different sets of shocks, assumptions about the agents' expectations and the labor market.

determinant for all cases that we consider in this paper. In contrast, the differences in the purpose for which the industry output is used and composition of labor force across industries appear to have only minor effects on the value of the multipliers. The major factors that influence the value of the multipliers in a small open economy certainly differ from a closed economy, where import shares are by definition not essential.

The industry-level analysis provides useful information as such, but ultimately also serves to better understand the determinants of multiplier values. Thus, the findings of our paper are relevant for fiscal policy, even though in practice the policy measures are unlikely to be confined to a single industry. In a unified framework, we discuss the short-term and long-term implications of a large set of fiscal policy interventions, both permanent and temporary.

The sensitivity of the spending multipliers with respect to the industry characteristics might to some extent explain the large variation in the estimates in the existing empirical works. The impact of the government spending shock depends crucially on the particular policy, or a set of policies considered in the various studies. Using just a narrowly defined set of spending shocks, such as unanticipated shocks to defence spending, is not sufficient to assess the multipliers in a broader context.

In this respect, our findings complement the existing literature that tries to explain the large variety in the multipliers found in the empirical studies. The estimates are sensitive to small changes in treatment, such as differences in measurement of multipliers, model set-up and parameterization, definitions of policy measures, and other dimensions, see Ramey (2019). Capek and Crespo Cuaresma (2020) demonstrate that the empirical SVAR estimates are also sensitive to other minor changes in modelling choices and data processing. Thus, throughout this paper, we pay attention to clear definitions of various multipliers and stick to concepts in line with the relevant literature. Moreover, there is a growing evidence stressing the asymmetric effects of the government spending with respect to the sign of the measure (Barnichon et al. 2020), and with respect to the state of the business cycle (Auerbach and Gorodnichenko 2012). In this paper, the effects of all policy shocks are symmetric.

One should stress that the focus of this study is not on the precise empirical estimation of the multipliers. Instead, we focus on the heterogeneity of the multipliers across industries and investment types. Our main findings about the heterogeneity and its sources turn out to be a robust feature of the model, as we show in a number of robustness exercises.

The rest of the paper is structured as follows. After discussing the related literature in section 3.1.1, we introduce the multi-industry New Keynesian small open economy model in section 3.2. We describe the data sources and calibration strategy in section 3.3. Section 3.4 presents the multipliers generated by the model and section 3.5 discusses the sources of the heterogeneity. Section 3.6 provides additional results on government investment. Section 3.7 concludes.

3.1.1 Related literature

The present paper studies the fiscal multipliers from the perspective of a New Keynesian dynamic general equilibrium model. Therefore, the literature review mostly focuses on this strand of the literature, omitting a large number of studies which use empirical methods, such as structural vector autoregression models or event studies. Various D(S)GE models are commonly used to estimate the impact of the policy interventions on the economy and are suitable for analysing the sensitivity of the effects with respect to different assumptions or characteristics of the economy, for examples see Brinca et al. (2016), Erceg and Lindé (2012), Corsetti et al. (2012).

Using comparatively small models, Hall (2009), Woodford (2011), and Christiano et al. (2011) describe the effects of fiscal policy shocks in a closed economy analytically. New Keynesian DSGE models of larger scale can also be used to simulate effects of fiscal policy, see the comparative studies from Coenen et al. (2012) and de Walque et al. (2015). De Walque et al. compare fiscal multipliers generated by fifteen dynamic macroeconomic models maintained within the European System of Central Banks, including both closed and open economies. They find that the differences in the size of the fiscal multipliers generated by the models can be traced back to the nature of fiscal shock and some country specific features, such as the share of liquidity-constrained consumers, financial frictions, and different degrees of price and wage rigidities among others. On the other hand, they find that some features are robust across the models. For example, most of the short-run multipliers are smaller than one, and temporary shocks generate higher short-run multipliers compared to the permanent changes. Coenen et al. (2012) study the effects of fiscal policy comparing seven models that are used by various prominent institutions, including the International Monetary Fund and the European Central Bank. They also find that the models share a number of robust implications. Temporary fiscal stimulus via public consumption or targeted transfers to constrained households generates the biggest short-run response of aggregate output. Again, persistent shocks generate considerably smaller multipliers compared to the temporary shocks.

In this paper, we focus our attention on small open economies within a monetary union, which considerably decreases the size of the relevant literature. The paper is most closely related to Schuster (2019) who also focuses on the case of Austria. Using a New Keynesian model, Schuster studies the sensitivity of various aggregate multipliers to a big number of model parameters including various fiscal instruments, preference and production function parameters and institutional set-up. The paper does not aspire to estimate the one "correct" value of the multiplier but rather focuses on explaining the mechanisms that determine the value of various multipliers. However, the benchmark model calibration in Schuster (2019) provides a natural point of reference which we also use to compare with the aggregate results of our model. Our paper differs from Schuster (2019) in that we build a disaggregated model and analyse the multipliers at the industry level. Other estimated New Keynesian models for Austria that help to calibrate our model are Breuss and Rabitsch (2009) and Fenz et al. (2012).

A number of survey and meta studies reports empirical estimates of fiscal multipliers, see e.g. Ramey (2019), Capek and Crespo Cuaresma (2020), Gechert (2015), and Ramey (2011). An important insight from these studies is that a considerable amount of cross-study variation in multipliers is due to differences in measurement of the multipliers. Indeed, it is often hard to compare the values between and within studies due to the differences in measurement of multipliers, modelling choices, parameterizations, definitions of the policy measures, and other dimensions.

This paper combines two important extensions of the New Keynesian model. First, we follow Galí et al. (2007) and Debortoli and Galí (2017), and model household heterogeneity using two types of households, one of which is credit-constrained. The two types of households differ in their marginal propensity to consume, which is an important determinant of the size of the multipliers, see also Farhi and Werning (2012), Brinca et al. (2016). Second, our paper builds on the growing strand of the literature on industry-level DSGE models, see Horvath (2000), Foerster et al. (2011), Atalay (2017), Smets et al. (2019), vom Lehn and Winberry (2020), and Molnárová and Reiter (2020). To the best of our knowledge, our model is unique in this strand in that it features a small open economy. Moreover, the present paper does not focus on the business cycle properties of the model, as we study the effects of isolated fiscal policy shocks.

3.2 Model

We build a multi-industry New Keynesian dynamic stochastic general equilibrium (DSGE) model of a small open economy within a monetary union. The model is calibrated such that it resembles the economic environment in Austria. Since we use the model for assessing the impact of individual government spending policies, we do not analyse unconditional second moments and do not use stochastic simulations of the model. However, the model is in principle suited to analyse the effects of standard aggregate shocks, e.g. monetary policy shocks and shocks to technology. We used conditional second moments for some of these shocks for calibration purposes.

The model economy consists of domestic (Austrian) households, firms, the government, and the rest of the world. The agents trade goods, production factors and financial assets. Figure 3.1 depicts the model environment in a simplified manner. The main components of the model include:

- Households, differentiated into credit constrained and non-credit constrained type.
- Production firms, differentiated into a big number of industries. The model economy consists of 74 industries that are connected through an input-output network.
- Government, conducting demand and supply side fiscal policies, modelled in a detailed way. Government spending policies are differentiated into government consumption (by industry), five types of government investment, and transfers.
- Tax system, resembling the most important tax revenues.
- International trade of goods and financial assets with the rest of the world.
- Monetary policy, set by an (external) monetary authority.
- Policy shocks.

The model described in this paper represents the stationary version of the economy, abstracting from deterministic economic growth and trend inflation. We solve the model by linearisation around the steady state.

3.2.1 Households

The economy is populated by a continuum of infinitely-lived households represented by a unit interval. Measure ω^K of the households is credit constrained, where $0 \leq \omega^K \leq 1$. Throughout

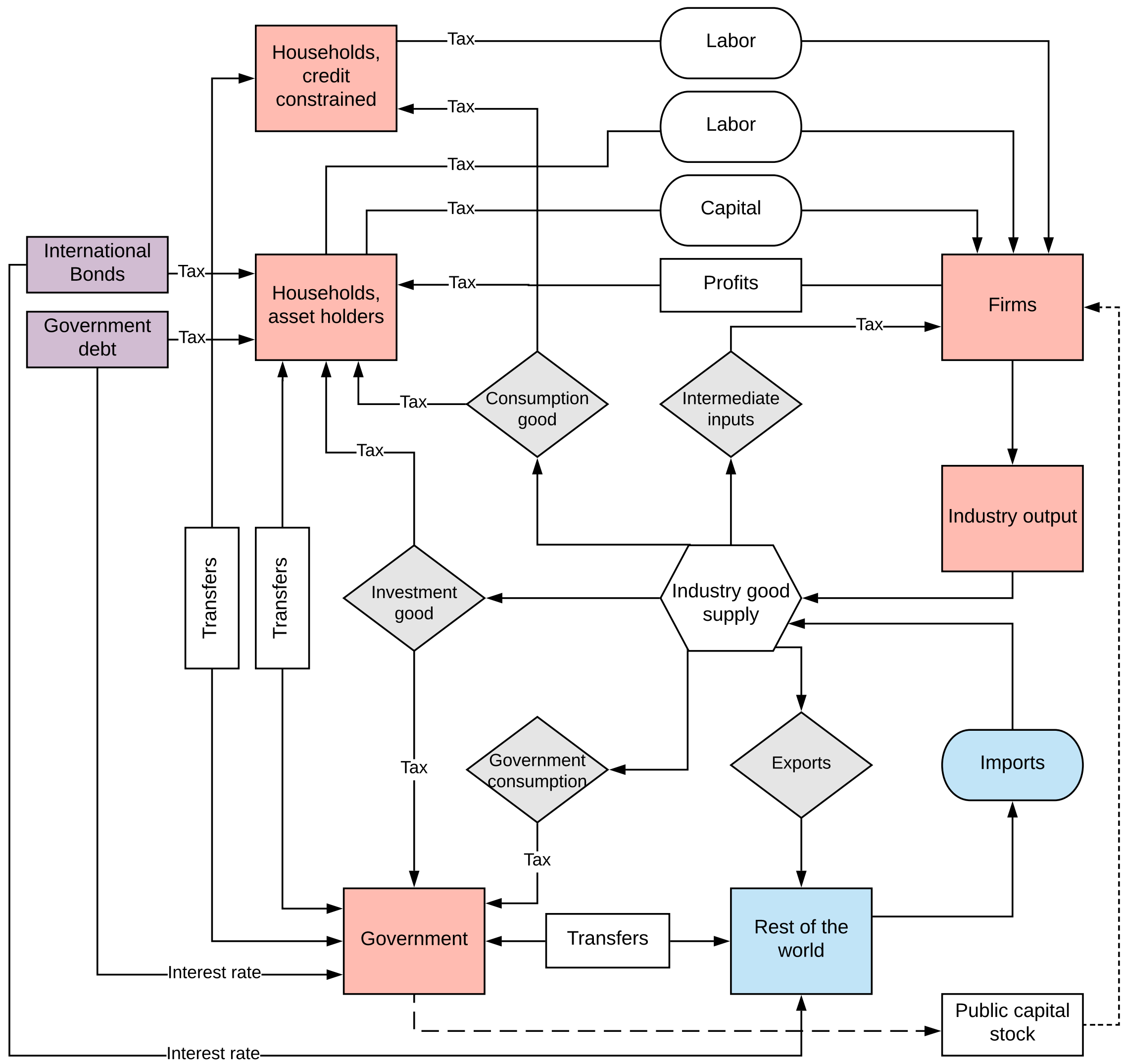

Figure 3.1: Model structure. Domestic agents (red), rest of the world (blue), uses of industry goods (grey), and financial assets (purple). Full lines represent financial transfers, which in most cases happen in exchange for goods, production factors, or assets. Dotted line symbolizes an influence on the economic environment without a financial compensation.

the paper, we refer to the credit constrained households as *Keynesian*. The remaining measure $1-\omega^K$ of the households are not credit constrained and we refer to them as *Ricardian*. All households provide labor input, earn wages, consume goods, pay taxes, and receive transfers from the government. Moreover, the Ricardian households also save resources in the form of risk-free international bonds and government bonds, own capital stock, and receive firm profits.

Household preferences are modelled in line with the majority of the contemporary macroeconomic literature. However, the utility function differs from the standard functional forms because of the industry structure of our model. Particularly, in the economy consisting of multiple industries, the households must decide not only *how much* labor they want to supply, but also *in which industries* they prefer to work. The utility function reflects both dimensions of the labor supply decision. The objective of the households is to maximize their expected utility,

$$\mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\ln C_t^S - \frac{\left(N_t^S\right)^{1+1/\eta}}{1+1/\eta} \right], \tag{3.1}$$

where $S \in \{K, R\}$ denotes Keynesian, resp. Ricardian type of household. In period t, the household consumes C_t^S units of the final *consumption good*. Parameter $\beta \in (0,1)$ denotes the discount rate and $\eta > 0$ is the elasticity of total labor supply N_t^S. We model the labor supply decision of households in line with Horvath (2000) and Bouakez et al. (2014). The households supply differentiated labor input (hours) $l_{i,t}^S$ into each of the I industries, denoted by $i = 1 \dots I$. Total labor input is given as

$$N_t^S = \left(\sum_{i=1}^{I} \nu_i^{N,S} l_{i,t}^S {}^{\frac{\sigma_N+1}{\sigma_N}} \right)^{\frac{\sigma_N}{\sigma_N+1}}. \tag{3.2}$$

Thus, household utility is decreasing in number of hours worked in each industry and households prefer to distribute the labor input across industries according to exogenously given weights. The weight $\nu_i^{N,S}$ determines the relative amount of labor input that the household wishes to supply into industry i. The elasticity parameter $\sigma_N > 0$ determines how strongly the weights affect the realised labor input allocation across industries. For σ_N approaching infinity, labor inputs in various industries are perfect substitutes as far as the household is concerned. For $\sigma_N < \infty$, households prefer to diversify their labor input, thus the labor input is not perfectly mobile across industries. This specification allows for industry-specific conditions, e.g. wages, while maintaining the two types of representative households.

The consumption good serves as the numeraire and all prices are expressed relative to its price before tax, P_t. The budget constraint of the Ricardian household is then formulated as

$$\begin{aligned}
&\left(\sum_{i=1}^{I}(1-\tau_{i,t}^{l,R})(1-\tau^{s,R})w_{i,t}^{R}l_{i,t}^{R}\right)+\left(\sum_{j=1}^{I^K}\left[(1-\tau^k)r_t^{k,j}+\tau^k\delta^j\right]\frac{K_{t-1}^{j}}{1-\omega^K}\right)+\\
&+\left[R_t^B-\tau^B(R_t^B-1)\right]\frac{B_{t-1}}{1-\omega^K}+\left[R_t^G-\tau^{BG}(R_t^G-1)\right]\frac{B_{t-1}^{G}}{1-\omega^K}+\\
&+(1-\tau^k)\frac{T_t}{1-\omega^K}+\frac{LST_t^R}{1-\omega^K}-\frac{ResT}{1-\omega^K}=\\
&=(1+\tau_t^C)C_t^R+\frac{1}{1-\omega^K}\left(\sum_{j=1}^{I^K}(1+\tau^{X,j})P_t^{X,j}X_t^{R,j}\right)+\frac{B_t}{1-\omega^K}+\frac{B_t^G}{1-\omega^K}.
\end{aligned}\tag{3.3}$$

Variable $w_{i,t}^S$ for $S\in\{R,K\}$ represents gross real industry-specific wage per unit of labor input $l_{i,t}^S$. K_t^j is private capital stock of type $j=1,\dots I^K$, which is determined at the end of period t. Gross real return on capital $r_t^{k,j}$ and depreciation rate δ^j also depend on the type of capital. $P_t^{X,j}$ is the relative price of investment good of type j compared to the consumption good, $X_t^{R,j}$ is gross private investment (of Ricardian households) into type j capital. Ricardian households can save in the form of internationally traded one-period risk-free bonds B_t, which yield gross real return R_t^B. Moreover, the households are assumed to hold the government bonds B_t^G at an exogenously given gross real interest rate R_t^G. T_t are aggregate firm profits. The households have to pay tax rates $\tau_{i,t}^{l,S}$, $\tau^{s,S}$, τ^k, τ^B, τ^{BG}, τ_t^C, and $\tau^{X,j}$, denoting the labor income tax, social insurance contributions, taxes on capital asset income, interest on private bonds, interest on government bonds, consumption, and investment good, respectively. Moreover, they pay residual lump sum taxes $ResT$ and receive lump-sum transfers from the government, LST_t^S.

Within the domestic economy, only Ricardian households trade the international risk-free bonds. Because the Ricardian households are all the same, the demand for the bond will be either positive or negative for all of them. Therefore, they are only able to trade the bond with the rest of the world. It follows that the total bond holdings must be equal to the net foreign asset position of the Ricardian households, which in turn equals the net foreign asset position of the whole domestic economy,

$$B_t=NFA_t.\tag{3.4}$$

The Keynesian households are excluded from all asset markets and thus can not transfer resources over time. Their budget constraint is given by

$$\left(\sum_{i=1}^{I}(1-\tau_{i,t}^{l,K})(1-\tau^{s,K})w_{i,t}^{K}l_{i,t}^{K}\right)+LST_t^K/\omega^K=(1+\tau_t^C)C_t^K.\tag{3.5}$$

3.2.2 Consumption good

The households consume a bundle of differentiated *industry goods* produced by a variety of industries at home and abroad,

$$C_t^S = \left(\sum_{i=1}^{I} v_i^{\frac{1}{\sigma_C}} c_{i,t}^{S\ \frac{\sigma_C - 1}{\sigma_C}} \right)^{\frac{\sigma_C}{\sigma_C - 1}}, \tag{3.6}$$

where $S \in \{R, K\}$, $c_{i,t}^S$ is the amount of industry i good that is used for consumption by the household of type S and v_i is the weight of good i in the consumption basket. Parameter $\sigma_C > 0$ represents the elasticity with which the households substitute between industry goods. The weights v_i are constant over time and calibrated to match the composition of household consumption expenditures from the input-output tables.
The nominal price of the consumption good before tax can be expressed as

$$P_t C_t^S = \sum_{i=1}^{I} p_{i,t}^{NOM} c_{i,t}^S, \tag{3.7}$$

where $p_{i,t}^{NOM}$ is the nominal price of industry good i. Given the prices of industry goods, the optimal demand for industry i good is iso-elastic, given by

$$c_{i,t}^S = v_i {p_{i,t}}^{-\sigma_C} C_t^S, \tag{3.8}$$

where $p_{i,t}$ is the relative price of good i compared to the price of the numeraire consumption good P_t, $p_{i,t} = p_{i,t}^{NOM}/P_t$. It follows from equations 3.7 and 3.8 that the relative prices satisfy

$$1 = \left(\sum_{i=1}^{I} v_i {p_{i,t}}^{1-\sigma_C} \right)^{\frac{1}{1-\sigma_C}}. \tag{3.9}$$

The government imposes a product tax on final consumption with rate τ_t^C. The consumption tax may be subject to exogenous policy shocks. We calibrate the steady state value τ^C such that it matches the average consumption tax revenues from private households, which depends on industry-specific tax rates available in the input-output tables. Thus, in steady state,

$$(1 + \tau^C)C = \sum_{i=1}^{I} (1 + \tau_i^c) p_i c_i. \tag{3.10}$$

The tax rate is the same for Ricardian and Keynesian households, as their consumption baskets have the same composition.

The assumption that there is a single tax rate that applies to all goods that are used for private consumption simplifies the calculations. The assumption has relatively mild effects on the results in the case where industry-specific shocks to household's demand are not considered. There are, however, small quantitative effects of this approach. Assuming the single tax rate biases the cost shares of individual goods, thus influencing the effects of price changes of individual goods on the aggregate prices.

3.2.3 Industry output

Each domestic industry consists of a continuum of monopolistically competitive firms represented by the unit interval. The differentiated *firm goods* aggregate to industry output according to

$$y_{i,t} = \left(\int_0^1 y_{ki,t}^{\frac{\sigma_I - 1}{\sigma_I}} dk \right)^{\frac{\sigma_I}{\sigma_I - 1}}, \tag{3.11}$$

where $y_{ki,t}$ denotes the output produced by an individual firm k in industry i and $\sigma_I > 0$ is the elasticity of substitution between the firm goods.

The industry output has five potential purposes. First, it composes the final *consumption good*. Second, it serves as *intermediate input* in the production of domestic firm goods. Third, it is used in the production of *investment goods* that build the domestic capital stock. Fourth, it is used for *government consumption*. Fifth, it is *exported*. The industries differ in the extent to which their output is used for each of these purposes. Throughout this paper, we refer to the share of industry output used for each of the purposes as *use-shares*.

The aggregator 3.11 implies iso-elastic demand for goods of firm k,

$$y_{ki,t} = \left(\frac{p_{ki,t}}{p_{i,t}^H} \right)^{-\sigma_I} y_{i,t}, \tag{3.12}$$

where $p_{ki,t}$ is the price set by firm k in industry i. The price of the domestically produced industry good $p_{i,t}^H$ can be expressed as

$$p_{i,t}^H = \left(\int_0^1 p_{ki,t}^{1-\sigma_I} dk \right)^{\frac{1}{\sigma_I - 1}}. \tag{3.13}$$

3.2.4 Firms

Monopolistically competitive domestic firms produce goods combining capital input, labor, and intermediate inputs. Firms maximize the expected discounted value of their future profits. In order to produce, the firms in industry i must pay the fixed cost $\Phi_i \geq 0$. All firms in an industry have access to the same technology and are ex ante the same. Therefore, in order to simplify the formulas, we omit the firm indices in the following firm-level equations. The gross output of a firm in industry i follows

$$y_{i,t} = J_t A_t z_{i,t} \left[\mu_{i,K}^{\frac{1}{\sigma_y}} k_{i,t}^{\frac{\sigma_y - 1}{\sigma_y}} + \mu_{i,L}^{\frac{1}{\sigma_y}} l_{i,t}^{\frac{\sigma_y - 1}{\sigma_y}} + \mu_{i,M}^{\frac{1}{\sigma_y}} M_{i,t}^{\frac{\sigma_y - 1}{\sigma_y}} \right]^{\frac{\sigma_y}{\sigma_y - 1}} - \Phi_i, \tag{3.14}$$

where A_t is exogenous aggregate technology that affects all industries. In contrast, $z_{i,t}$ is industry-specific technology that only affects firms in industry i. J_t denotes the level of public infrastructure, which depends on the stock of public capital K^G_{t-1},

$$J_t = \left(\frac{K^G_{t-1}}{K^G} \right)^{\gamma_J},$$

where K^G is the steady state value of the stock of public capital and parameter $\gamma_J > 0$ drives the sensitivity of firm output to changes in public infrastructure. The production factors are combined with elasticity of substitution $\sigma_y > 0$.

Firms differentiate between labor input from Keynesian and Ricardian households and combine them into labor input composite

$$l_{i,t} = \left((1-\omega^K)(l^R_{i,t})^{\frac{\sigma_l - 1}{\sigma_l}} + \omega^K (a^K_i)^{\frac{1}{\sigma_l}} (l^K_{i,t})^{\frac{\sigma_l - 1}{\sigma_l}} \right)^{\frac{\sigma_l}{\sigma_l - 1}}, \tag{3.15}$$

where $\sigma_l > 0$ is the elasticity of substitution between types of labor input and $(a^K_i)^{\frac{1}{\sigma_l}}$ is the relative productivity of Keynesian workers.

Capital input composite $k_{i,t}$ is produced from I^K differentiated capital types with constant returns to scale technology

$$k_{i,t} = \left(\sum_{j=1}^{I^K} {\chi^j}^{\frac{1}{\sigma_k}} {k^j_{i,t}}^{\frac{\sigma_k - 1}{\sigma_k}} \right)^{\frac{\sigma_k}{\sigma_k - 1}}, \tag{3.16}$$

where $k^j_{i,t}$ denotes the capital input of type j that a firm in industry i uses to produce its output. Parameter $\sigma_k > 0$ is the elasticity of substitution between the capital types. Weights $\chi^j \geq 0$ determine the relative importance of capital inputs of different types. We calibrate the parameters χ^j to reflect the average capital composition implied by the input-output tables, see the discussion in appendix 3.C for detail.

The intermediate input composite $M_{i,t}$ is constructed from industry goods with constant returns to scale technology

$$M_{i,t} = \left(\sum_{j=1}^{I} {\alpha_{ji}}^{\frac{1}{\sigma_M}} {m_{ji,t}}^{\frac{\sigma_M - 1}{\sigma_M}} \right)^{\frac{\sigma_M}{\sigma_M - 1}}, \tag{3.17}$$

where $m_{ji,t}$ denotes the intermediate good from industry j that a firm in industry i uses to produce its output. The parameter $\sigma_M > 0$ is the elasticity of substitution between intermediate inputs from different industries. The weights $\alpha_{ji} \geq 0$ determine the relative importance of intermediate inputs from various industries. We calibrate the parameters α_{ji} to reflect the average composition from the input-output tables. Intermediate inputs are subject to industry-specific tax τ^M_i, identified as the weighted average of industry-level steady state product taxes

$$(1+\tau^{M,i}) P^M_i M_i = \sum_{j=1}^{I} (1+\tau^m_{ji}) p_j m_{ji}, \tag{3.18}$$

where $P^M_{i,t}$ is the relative price of the intermediate input composite $M_{i,t}$.

Price setting

The firms face standard Calvo-type rigidities when setting the prices. Since the firms in industry i are ex ante identical, they all choose the same optimal price $p_{i,t}^*$ conditional on adjusting the price in period t. Substituting into 3.13, the price of industry i goods evolves according to

$$p_{i,t}^H = \left[\theta_i \left(\frac{p_{i,t-1}^H}{\pi_t} \right)^{1-\sigma_I} + (1-\theta_i) {p_{i,t}^*}^{1-\sigma_I} \right]^{\frac{1}{1-\sigma_I}}, \tag{3.19}$$

where $\pi_t = P_t/P_{t-1}$ denotes the price inflation and $\theta_i \in [0,1]$ is the probability that a firm is not allowed to adjust the price in a given period. The degree of price stickiness is likely to differ across industries, see e.g. Bouakez et al. (2014). However, the identification of the parameter θ_i at the industry level is difficult. Moreover, Schuster (2019) shows that the value of this parameter only has a moderate impact on the value of the government spending multipliers. Therefore, we calibrate the degree of price stickiness to be the same across all industries.

In nominal terms, the price setting firm maximizes

$$\mathrm{E}_t \sum_{s=0}^{\infty} {\theta_i}^s Q_{t,t+s} \left[y_{i,t+s|t} \cdot p_{i,t}^{NOM} - \mathcal{C}_{i,t+s|t} \right], \tag{3.20}$$

where $p_{i,t}^{NOM}$ is the nominal price set at time t and $y_{i,t+s|t}$ is period $t+s$ demand for goods of a firm in industry i that was last setting its prices in period t. $Q_{t,t+s}$ is nominal discount factor between periods t and $t+s$, defined as

$$Q_{t,t+s} = \beta^s \frac{\lambda_{t+s}}{\lambda_t} \frac{P_t}{P_{t+s}}, \tag{3.21}$$

where λ_t denotes the marginal utility of consumption of the Ricardian household at period t. $\mathcal{C}_{i,t+s|t}$ are firm nominal costs of producing output $y_{i,t+s|t}$. Abstracting from the fixed costs, the firm production is constant returns to scale. Thus, we can express the nominal costs in terms of the real marginal costs $RMC_{i,t}$ as

$$\mathcal{C}_{i,t+s|t} = P_{t+s} RMC_{i,t+s} (y_{i,t+s|t} + \Phi_i).$$

3.2.5 Capital and investment

Both public and private capital stocks of each type $j = 1, 2, ...I^K$ are built using specialized investment goods X_t^j. The formation of the investment good of type j follows

$$X_t^j = \left(\sum_{i=1}^{I} {\nu_i^{X,j}}^{\frac{1}{\sigma_X}} {x_{i,t}^j}^{\frac{\sigma_X - 1}{\sigma_X}} \right)^{\frac{\sigma_X}{\sigma_X - 1}},$$

where $x_{i,t}^j$ is the amount of industry i good that is used for production of the investment good of type j, $\sigma_X > 0$ is the elasticity of substitution between industry goods and weight parameters $\nu_i^{X,j}$ drive the weight of industry i good in the investment good of type j. Given the prices of industry goods, an optimizing investor chooses

$$x_{i,t}^{j} = \nu_i^{X,j} \left(\frac{p_{i,t}}{P_t^{X,j}} \right)^{-\sigma_X} X_t^j, \tag{3.22}$$

where the relative price of investment good j can be expressed as an aggregate of the relative prices of intermediate goods,

$$P_t^{X,j} = \left(\sum_{i=1}^{I} \nu_i^{X,j} {p_{i,t}}^{1-\sigma_X} \right)^{\frac{1}{1-\sigma_X}}. \tag{3.23}$$

Both private investment $X_t^{R,j}$ and public investment $X_t^{G,j}$ use the same investment good X_t^j, thus

$$X_t^j = X_t^{R,j} + X_t^{G,j}. \tag{3.24}$$

Adjustment of the private capital stock of each type is subject to quadratic adjustment costs formulated as in Hayashi (1982). The costs are quadratic in investment intensity ι_t^j, defined as

$$X_t^{R,j} = \iota_t^j K_{t-1}^j. \tag{3.25}$$

The aggregate private capital stock of each type evolves according to

$$K_t^j = (1-\delta^j) K_{t-1}^j + \phi(\iota_t^j) K_{t-1}^j. \tag{3.26}$$

Thus, for any investment intensity ι_t^j, the part $\phi(\iota_t^j)K_{t-1}^j$ that is added to the capital stock is given by

$$\phi(\iota_t^j) = \iota_t^j - \kappa(\iota_t^j - \delta^j)^2,$$

where the depreciation rates δ^j vary across capital types. Cost parameter κ determines the size of the adjustment costs.

This formulation of capital adjustment costs is equivalent to several other ways of introducing convex adjustment costs, cf. Wang and Wen (2010). While the aggregate capital stock of each type in the model is rigid, there are no frictions to capital mobility across industries.

The public capital stocks $K_t^{G,j}$ evolve according to

$$K_t^{G,j} = (1-\delta^j) K_{t-1}^{G,j} + X_t^{G,j}, \tag{3.27}$$

where we assume the same depreciation rate as for the private capital and no capital adjustment costs for the public capital stock. The latter assumption is not important for the results, as the impact of public investment on aggregate productivity is determined through another free parameter, γ^J.

The total government capital stock is formed from the differentiated capital types with constant returns to scale technology

$$K_t^G = \left(\sum_{j=1}^{I^K} \chi^{j\,\frac{1}{\sigma_k}} K_t^{G,j\,\frac{\sigma_k - 1}{\sigma_k}} \right)^{\frac{\sigma_k}{\sigma_k - 1}}. \tag{3.28}$$

The elasticity of substitution between the capital types σ_k and weights χ^j are the same as for the private capital.

3.2.6 Government

The government collects taxes and spends resources on public consumption, investment, lump sum transfers to households and repaying the interest on its debt. The policy measures considered in this paper may directly affect government consumption, investment, transfers or tax rates in the form of exogenous policy shocks. Section 3.2.10 describes the shocks in detail.

The government consumption and investment are assumed to be exogenously given. Government consumption of good i follows

$$c_{i,t}^G = c_{i,ss}^G + \frac{d_{i,t}^{cG}}{(1 + \tau^{CG}) p_{i,t}}, \tag{3.29}$$

where $c_{i,ss}^G$ is the steady state spending on good i, and $d_{i,t}^{CG}$ is the government consumption spending shock on goods of industry i. Notice that the shocks are expressed in terms of government spending on consumption before tax. It follows that the aggregate government spending on consumption before tax is

$$C_t^G = \sum_i p_{i,t} c_{i,t}^G. \tag{3.30}$$

In steady state, expenditure shares of industry i goods in total government consumption are calibrated to match the data and we denote the shares by ν_i^{CG}. When discussing the *aggregate* shock to government consumption, we assume that the government is allocating its consumption such that the industry shares stay the same.

While government consumption does not directly influence the welfare of the households, government investment affects the aggregate productivity, therefore influencing their expected lifetime wealth. Government investment in type j capital follows

$$X_t^{G,j} = X_{ss}^{G,j} + \frac{d_{j,t}^{XG}}{(1 + \tau^{X,j}) P_t^{X,j}}, \tag{3.31}$$

where $X_{ss}^{G,j}$ is the steady state investment of type j, $d_{j,t}^{XG}$ is the corresponding government investment spending shock. When discussing the *aggregate* shock to government investment, we assume that the government is allocating its consumption such that the expenditure shares stay constant across investment types.

The government makes lump sum transfers to Keynesian households, LST_t^K, and Ricardian households, LST_t^R, which are subject to government spending shocks,

$$LST_t^K = LST_{ss}^K + d_t^{LST^K}, \tag{3.32}$$

$$LST_t^R = LST_{ss}^R + d_t^{LST^R}. \tag{3.33}$$

The government can borrow or lend resources in the specialised bond market for a given gross real interest rate R_t^G. We assume that domestic (Ricardian) households clear the government bonds market in each period. Alternative assumptions about the market clearing that we tested lead to similar model outcomes. The budget constraint of the government can be expressed as

$$B_t^G = B_{t-1}^G R_t^G + (1+\tau^{CG})C_t^G + \left(\sum_{j=1}^{I^K}(1+\tau^{X,j})P_t^{X,j}X_t^{G,j}\right) + LST_t - TaxRev_t, \tag{3.34}$$

where $TaxRev_t$ are the total tax revenues of the government and $LST_t = LST_t^K + LST_t^R$ are the total lump sum transfers to the domestic households.

As the composition of investment good of each type is the same for government and private investment, the tax rates $\tau^{X,j}$ are the same as in the private sector. The government consumption, however, has composition that differs from the private consumption. Therefore, the government faces a different consumption tax rate τ^{CG}, identified as the average rate paid by the government in the steady state,

$$(1+\tau^{CG})C^G = \sum_{i=1}^{I}(1+\tau_i^{cg})p_i c_i^G. \tag{3.35}$$

Total tax revenues of the government are given by

$$\begin{aligned} TaxRev_t = \sum_{i=1}^{I} & \left[(\tau^{s,R} + \tau_{i,t}^{l,R}(1-\tau^{s,R}))(1-\omega^K)w_{i,t}^R l_{i,t}^R + (\tau^{s,K} + \tau_{i,t}^{l,K}(1-\tau^{s,K}))\omega^K w_{i,t}^K l_{i,t}^K\right] \\ & + \tau_t^C\left[(1-\omega^K)C_t^R + \omega^K C_t^K\right] + \tau^{CG}C_t^G + \sum_{j=1}^{I^K}\tau^{X,j}P_t^{X,j}X_t^j + \sum_{i=1}^{I}\tau^{M,i}P_t^{M,i}M_t^i \\ & + \tau^k\sum_{j=1}^{I^K}(r_t^{k,j} - \delta^j)K_{t-1}^j + \tau^k T_t + \tau^B(R_t^B - 1)NFA_{t-1} + \tau^{BG}(R_t^G - 1)B_{t-1}^G \\ & + ResT. \end{aligned} \tag{3.36}$$

In the benchmark calibration of the model, the labor income tax rates are only differentiated by household type and kept constant across industries. The labor income tax rates are time dependent and we use them as the fiscal instrument that ensures the stability of the model. The labor income tax rates adjust endogenously in reaction to the level of government debt, following

$$\tau_{i,t}^{l,S} = \tau_{i,ss}^{l,S} + \rho^{\tau_l}(\tau_{i,t-1}^{l,S} - \tau_{i,ss}^{l,S}) + \gamma^{\tau_l}\frac{B_{t-1}^G - B_{ss}^G}{VA_{t-1}}. \tag{3.37}$$

We calibrate the parameters ρ^{τ_l} and γ^{τ_l} such that the endogenous reaction to the level of government debt is extremely slow. Thus, even though we use a distortionary fiscal instrument (labor income tax), we effectively isolate the effects of the policy shocks from the stabilizing budgetary effects of the fiscal instrument.

3.2.7 International trade

The domestic economy trades goods and financial assets with the rest of the world. Both home economy and the rest of the world are parts of a monetary union and share a common currency. The rest of the world consumes home and foreign goods, which constitute the consumption basket C_t^F with corresponding price index P_t^F, expressed in terms of the numeraire home consumption good C_t. Unlike the home economy, the rest of the world is big. Thus, the nominal price of the foreign consumption basket, P_t^{FNOM}, is not affected by the prices in the home economy and can be treated as a constant (normalized to one). However, the trade volumes between the home economy and the rest of the world depend on relative prices between home and foreign goods, which determine the real exchange rate

$$RER_t = P_t/P_t^{FNOM} = 1/P_t^F. \tag{3.38}$$

As the nominal price level in the rest of the world is constant, the real exchange rate can be expressed recursively as

$$RER_t = RER_{t-1}\pi_t. \tag{3.39}$$

Exports

We assume that the real exports from domestic industries to the rest of the world follow a reduced-form demand function

$$\begin{aligned} ex_{i,t} &= ex_i^{ss}(p_{i,t}^H RER_t)^{-\upsilon_E} & (3.40)\\ &= ex_i^{ss}(p_{i,t}^H/P_t^F)^{-\upsilon_E}, & (3.41) \end{aligned}$$

where $\upsilon_E > 0$ is the price elasticity of exports.

Imports

Each of the industry goods is used in the home economy for one of the five purposes (private consumption, government consumption, investment, intermediate inputs, exports). For each of these purposes, both goods produced at home and abroad are required. The total amount of good i available for each of the uses, $g \in \{c^K, c^R, c^G, x, ex, m\}$, is a CES composite of domestic and foreign goods,

$$g_{i,t} = \left((1-\alpha_i^{it})^{\frac{1}{\upsilon_A}} g_{i,t}^{H\,\frac{\upsilon_A-1}{\upsilon_A}} + \alpha_i^{it\,\frac{1}{\upsilon_A}} g_{i,t}^{F\,\frac{\upsilon_A-1}{\upsilon_A}}\right)^{\frac{\upsilon_A}{\upsilon_A-1}}, \tag{3.42}$$

where α_i^{it} is a parameter that pins down the import intensity of the industry i. Parameter $\upsilon_A > 0$ is the Armington elasticity which measures the sensitivity of imports to relative prices. Given the price of home-produced good, $p_{i,t}^H$, and the price of foreign-produced good, $p_{i,t}^F$, both expressed in terms of domestic consumption good C_t, the optimal demand for domestic and foreign goods follows

$$g_{i,t}^H = (1-\alpha_i^{it})\left(\frac{p_{i,t}^H}{p_{i,t}}\right)^{-\upsilon_A} g_{i,t}, \tag{3.43}$$

$$g_{i,t}^F = \alpha_i^{it}\left(\frac{p_{i,t}^F}{p_{i,t}}\right)^{-\upsilon_A} g_{i,t} = \alpha_i^{it}\left(p_{i,t}RER_t\right)^{\upsilon_A} g_{i,t}, \tag{3.44}$$

where industry price (index) is given by

$$p_{i,t} = \left((1-\alpha_i^{it}){p_{i,t}^H}^{1-\upsilon_A} + \alpha_i^{it}{p_{i,t}^F}^{1-\upsilon_A}\right)^{\frac{1}{1-\upsilon_A}}, \tag{3.45}$$

and

$$p_{i,t}^F = p_{ss,t}^F/RER_t. \tag{3.46}$$

Since equation 3.44 holds for each use of industry goods separately, the total imports follow

$$im_{i,t} = \alpha_i^{it}\left(p_{i,t}RER_t\right)^{\upsilon_A}(c_{i,t} + c_{i,t}^G + \sum_{j=1}^{I^K} x_{i,t}^j + \sum_{k=1}^{I} m_{ik,t} + ex_{i,t}), \tag{3.47}$$

where

$$c_{i,t} = \omega^K c_{i,t}^K + (1-\omega^K)c_{i,t}^R. \tag{3.48}$$

Net foreign assets

Foreign assets are held by the Ricardian households in the form of one-period risk-free nominal bonds. The net foreign asset position of the Ricardian households follows

$$NFA_t = NFA_{t-1}R_t^B + NetExp_t, \tag{3.49}$$

where the real value of net exports $NetExp_t$ is

$$NetExp_t = \sum_{i=1}^{I}(p_{i,t}ex_{i,t} - p_{i,t}^F im_{i,t}). \tag{3.50}$$

3.2.8 Monetary policy

The monetary union shares a common monetary policy which does not react to conditions in the home economy. We assume that the monetary authority sets an exogenously given nominal interest rate

$$R_t = R^*. \tag{3.51}$$

We assume for simplicity that R^* is chosen such that there exists a zero-inflation steady state for the home economy. The real interest rate on international bonds follows from the nominal rate, $R_t^B = R_{t-1}/\pi_t$.

3.2.9 Wage rigidity

The hourly wages in the model are subject to a real rigidity, a property which is commonly featured in DSGE models in order to improve their empirical performance. The real wage rigidity channel on one hand stabilizes the private demand through the income effect and works against the stabilizing role of prices in general equilibrium on the other hand. We implement the wage rigidity in reduced form by introducing a wedge in the optimal labor supply decision of households outside of the steady state, see appendix 3.B for detail.

3.2.10 Shocks

Policy shocks

Each of the fiscal policy shocks $d_t^{\times}$ is modelled as an autoregressive process

$$d_t^{\times} = \rho d_{t-1}^{\times} + \epsilon_t^{d^{\times}}, \tag{3.52}$$

where $\epsilon_t^{d^{\times}}$ is an unanticipated expansionary disturbance term and ρ is the persistence parameter. The policy shocks in the model are $d_{i,t}^{cG}$, $d_{j,t}^{XG}$, $d_t^{LST^K}$, $d_t^{LST^R}$, and $d_t^{\tau^C}$.

Non-policy shocks

Small and medium-size DSGE models typically focus on the cyclical fluctuations of economic variables and feature a variety of shocks that drive the business cycles. Although not directly applicable for the results of this paper, the model allows for a variety of non-policy macroeconomic demand and supply side shocks at the aggregate and industry level. Productivity shocks in the model were used for calibration purposes.

- Aggregate technology follows AR(1) process

$$\log(A_t) = \rho^A \log(A_{t-1}) + \epsilon_t^A, \qquad \epsilon_t^A \sim \mathcal{N}(0, \sigma_A^2), \tag{3.53}$$

- Industry technology follows AR(1) process

$$\log(z_{i,t}) = \rho^z \log(z_{i,t-1}) + \epsilon_{i,t}^z \qquad \epsilon_{i,t}^z \sim \mathcal{N}(0, \sigma_{z,i}^2). \tag{3.54}$$

3.2.11 Market clearing and value added

All markets clear in equilibrium. In particular, for each intermediate good i, the total production plus imports equals the amount of good i used for final consumption, government consumption, investment, intermediate inputs to production in all industries and exports,

$$y_{i,t} = c_{i,t} + c_{i,t}^G + \sum_{j=1}^{I^K} x_{ji,t} + \sum_{k=1}^{I} m_{ik,t} + ex_{i,t} - im_{i,t}. \tag{3.55}$$

The firm-level factor inputs clear the industry-level factor supply.

Aggregate value added is given by

$$VA_t = C_t + C_t^G + \sum_{j=1}^{I^K} P_{j,t}^X X_{j,t} + NetExp_t - \sum_{i=1}^{I} \tau_i^M P_i^M M_i. \tag{3.56}$$

Gross domestic product is defined as

$$GDP_t = (1+\tau_t^C)C_t + (1+\tau^{CG})C_t^G + \sum_{j=1}^{I^K}(1+\tau^{X,j})P_{j,t}^X X_{j,t} + NetExp_t. \tag{3.57}$$

3.3 Data and Calibration

3.3.1 Data sources

The primary data source are the Austrian input-output tables (IOT) from years 2012 - 2014 supplemented by other data sources, including the national accounts, national tax list, and EU Statistics on income and living conditions (EU-SILC).

Austrian input-output tables. We use the information from tables *28 - Input-output table at basic prices, domestic output and imports* and *27 - Employment (Products)* published by Statistics Austria. Table 27 provides information on employment and hours worked in each industry, separately for employed and self-employed persons. Table 28 provides information on the input-output structure of the economy which includes industry output, use of intermediate inputs and other production factors (make-side), product taxes, use of industry output differentiated by purpose (use-side) and imports.[2]

The information from the input-output tables is used to calibrate the steady state of the model economy. To minimize the effect of short term fluctuations, we use averages over the IOT information from years 2012, 2013 and 2014.

Other data sources. To characterise the two types of households we use the data from the 2016 EU Statistics on income and living conditions in Austria published by Statistics Austria, (StatAT 2017). The EU-SILC database gathers the information on income, government transfers, and other income-related statistics from 6,000 individual households representative of all 3.9 million households in Austria.

For public and private investment and unemployment benefit payments we use the information from the national accounts, tables 57 and D.62, as reported by the Austrian statistical office (StatAT 2018).

[2]The IOT published by Statistics Austria are product-based, in contrast to the industry-based IOT reported by some other sources, e.g. the WIOD database. The product-based IOT provide a more suitable counterpart to the model specification. However, some other data inputs, e.g. EU-SILC data are reported at the level of industries. For the purposes of the paper, the differences between the classifications are within an acceptable range. For example, in case of industry-level employment, only three industries/product groups show any substantial discrepancies.

We also use the information on tax revenues from the National Tax List published by Statistics Austria, see table *Steuern und Sozialbeitraege in Oesterreich: Einzelsteuerliste / National Tax List*. The data set includes the information on annual tax revenues and social security contributions disaggregated by the type of tax. In line with the IOT we use the information from 2012 to 2014.

3.3.2 Calibration

We calibrate the model at quarterly frequency. In line with the Austrian IOT, the model distinguishes 74 industries and 5 types of capital. Table 3.1 summarizes model parameters and calibration targets.

The steady state of the model economy is pinned down by a number of weight parameters, tax rates, and other parameters which we calibrate to directly match their counterparts in the Austrian data. The parameters and data sources are listed in table 3.1. The detailed description of how we constructed the target values can be found in appendix 3.C.

We define Keynesian households as those with equivalized disposable income below the median and gross capital income of less than 100 Euro per year. According to the EU-SILC data, this characterization applies to roughly 36% of the Austrian households. We classify the remaining 64% of the households as Ricardian. We also utilize the EU-SILC data to calibrate the differences between Keynesian and Ricardian households in hours worked, hourly wages, and government transfers.

We calibrate the nine different types of tax rates in the model such that the implied tax revenue of each tax matches the data from the National Tax List. Thus, we implicitly assume that the average tax rates equal the marginal tax rates which influence the economic decisions. Such assumption is not innocuous, but relatively common in the DSGE literature, see Coenen et al. (2008), Gadatsch et al. (2016), Adolfson et al. (2013).[3]

Other parameters The majority of the remaining parameters are calibrated to values commonly used in the existing macroeconomic literature. The household discount rate β is set such that it implies the steady state real net interest rate of 2%. We conservatively assume that the effective real interest rate on government bonds is moderately above the OECD long-term projection (OECD 2018), namely 0.5% annually above the trend growth and inflation. The choice of this parameter influences the value of the government debt in the long run, but has otherwise a small effect on the model results. We calibrate the steady state debt-to-GDP ratio B^G to 60%, which is a declared long run target of the Austrian government. Varying the value of the parameter within a reasonable range has negligible effects on the results.

The elasticity of substitution between firm goods σ_I is set such that the steady state markups equal 10%, which is a standard value used in the New Keynesian DSGE models. We choose the steady state firm profits such that the implied capital depreciation rates approximately match the rates reported by the Statistics Austria adjusted for growth, see appendix 3.C for

[3]Some recent studies assume marginal tax rates to be equal to the average tax rates with the exception of labor income tax, see Brinca et al. (2016), Stähler and Thomas (2012). In our model, the labor income tax rates differ between Keynesian and Ricardian households, capturing a part of the heterogeneity in the effective tax rates.

Calibration summary			
Parameter	Symbol	Value	Target/Source
Elasticities			
Intra-industry substitution	σ_I	11	10% markup
Consumption good subst.	σ_C	0.4	Molnárová and Reiter (2020)
Investment good subst.	σ_X	0.4	equals σ_C
Production factors subst.	σ_y	0.39	Molnárová and Reiter (2020)
Intermediate inputs subst.	σ_M	0.75	Molnárová and Reiter (2020)
Labor input types subst.	σ_l	0.5	low substitutability
Capital types subst.	σ_k	2	medium substitutability
Industry labor input subst.	σ_N	2	Molnárová and Reiter (2020)
Total labor input	η	0.5	standard
Import (Armington)	υ_A	2.4	Fenz et al. (2012), Imbs and Mejean (2015)
Export	υ_E	2.4	equals import
Taxes and transfers			
Product tax, household consumption	τ_{ss}^C	0.15	tax revenues, IOT
Product tax, government consumption	τ^{CG}	0.01	tax revenues, IOT
Product tax, investment good	$\tau^{X,j}$		tax revenues, IOT
Product tax, intermediate inputs	$\tau^{M,i}$		tax revenues, IOT
Asset income, capital and profits	τ^k	0.23	tax revenues, National Tax List
Asset income, interest on private bonds	τ^B	0.47	tax revenues, National Tax List
Asset income, interest on government bonds	τ^{BG}	0.00	normalization
Social insurance contribution rate	$\tau^{s,R/K}$	0.29	tax revenues, National Tax List, adjustment
Labor income, Ricardian households	$\tau_{ss}^{l,R}$	0.32	tax revenues, National Tax List, EU-SILC
Labor income, Keynesian households	$\tau_{ss}^{l,K}$	0.17	tax revenues, National Tax List, EU-SILC
Total tax revenues, percentage of value added	$TaxRev_{ss}$	48.50	total tax revenues, National Tax List
Residual tax, percentage of value added	$ResT$	1.94	total tax revenues, National Tax List
Steady state weights			
Import intensity	α_i^{it}		cost shares IOT, import shares
Production factor weights	$\mu_{\times,i}$		cost shares IOT, production factors
Intermediate inputs weights	α_{ji}		cost shares IOT, intermediate inputs
Household consumption weights	v_i		cost shares IOT, private consumption
Government consumption weights	ν_i^{CG}		cost shares IOT, government consumption
Investment good weights	$\nu_i^{X,j}$		cost shares IOT, investment by type
Export weights	ν_i^{EXPT}		cost shares IOT, exports
Disutility parameter: industry-specific labor	$\nu_i^{N,S}$		hours/wages IOT, EU-SILC
Relative productivity of Keynesian households	a_i^K		relative wages, EU-SILC
Other			
Share of Keynesian households	ω^K	0.359	EU-SILC, own definition
Discount factor	β	0.995	2% annual interest rate
Capital depreciation	δ^j		StatAT (2018)
Adjustment cost capital	κ	2	cond. relative volatility of investment
Productivity sensitivity to public infrastructure	γ^J	0.015	same productivity as private investment
Price stickiness	θ_i	0.75	standard
Wage stickiness	ω	0.75	relative volatility wages and consumption
Gross return on government bonds	R^G	0.5%	low annual rate
Steady state government debt, perc. of value added	B_{ss}^G	67.3	declared target
Steady state profit share, perc. of value added	$shProf$	4.5	IOT, StatAT (2018)
Autocorrelation, permanent policy shocks	ρ	0.99	persistent
Autocorrelation, temporary policy shocks	ρ	0.7	cumulative effect 95% after 2 years
Autocorrelation, technology shocks	ρ^A	0.95	standard
Fiscal instrument persistence	ρ^{τ_l}	0.995	high persistence
Fiscal instrument strength	γ^{τ_l}	0.005	weak reaction
Number of industries	I	74	IOT classification
Number of types of capital	I^K	5	IOT classification

Table 3.1: Calibration summary

detail. The capital adjustment costs parameter κ is calibrated such that the response to an aggregate technology shock of investment is about 3.5 times that of value added. The sensitivity of productivity to public infrastructure γ^J is chosen such that the effectivity of public investment is the same as for private investment. The value is within the range considered in the international literature, very close to Stähler and Thomas (2012). The calibration implies government investment multipliers (short and long run) in line with the existing DSGE models.[4] In line with the literature standard we set the Calvo parameter for price rigidity θ_i to 0.75 for all industries. We calibrate the wage rigidity parameter ω such that it delivers a reasonable compromise between the volatility of average wages relative to output and fluctuations of consumer price inflation.

We calibrate the import elasticity parameter υ_A to 2.4, in line with the estimated DSGE model of the Austrian economy in Fenz et al. (2012) and within the range typically estimated in the international literature, see for example Imbs and Mejean (2015). Although export elasticities of a small open economy are likely to be higher than import elasticities, we use the same value for υ_E. Values of the Frisch elasticity of labor supply η have been the subject of extensive discussion in both academic and applied macroeconomic literature. The New Keynesian literature in the recent years mostly focused on values close to 0.5, see e.g. de Walque et al. (2015).

Our model also features several elasticities which pin down the substitution between production factors and outputs across industries, which are less standard in the macroeconomic literature. Molnárová and Reiter (2020) identify the values of the substitution elasticities using a New Keynesian model of the U.S. economy. As the necessary industry-specific longitudinal data are not available for Austria, we calibrate the substitution elasticities based on these previous results.

The elasticity parameter σ_N determines the reallocation of labor across industries. Molnárová and Reiter (2020) identify the value of σ_N significantly above one based on the relative unconditional volatility of industry hours. For Austria, we calibrate the parameter $\sigma_N = 2$, implying somewhat less flexible adjustment of the labor supply compared to the U.S. They identify the elasticity of substitution between production factors σ_y based on the relative unconditional volatility of factor shares in the U.S. economy. The results presented in this paper are very robust with respect to elasticities of substitution between industry goods σ_M, σ_X and σ_C. The values are comparable with other industry-level models, see e.g. Atalay (2017), Huo et al. (2019).

We set the elasticity of substitution between labor types σ_l to a low value, which highlights the potential role of industry differences in Keynesian labor share. Model results are very robust with respect to the value of the elasticity of substitution between capital types σ_k. We calibrate the parameter somewhat arbitrarily to a medium value of 2.

We choose a very rigid response of the fiscal instrument (labor income tax rate), setting parameters ρ^{τ_l} and γ^{τ_l} very close to 1 and 0, respectively. The persistence parameter of the policy shocks is set to 0.99 for permanent shocks, and to 0.7 for temporary shocks. The value of 0.7 implies that around 75% of the cumulative effect of the shock happens within the first year and around 95% happens within the initial two years after impact.

[4] See de Walque et al. 2015, Stähler and Thomas 2012, Roeger and in 't Veld 2009

3.4 Fiscal multipliers

We now turn our attention to the fiscal multipliers generated by the model. We first introduce various concepts of multipliers which we discuss in the rest of the paper. Second, we present the multipliers generated by the standard aggregate shocks. We confirm that the model generates aggregate multipliers within the range identified in the literature and in line with the existing studies focusing on Austria. Third, we show that the model predicts a large variation in multipliers across industries.

3.4.1 Concepts of multipliers

The economic impact of fiscal policy measures is commonly assessed using some kind of fiscal multipliers. Loosely described, multipliers measure the change of the macroeconomic outcomes relative to the size of the policy intervention. However, there are differences in the exact definition of multipliers, and these differences can have substantial impact on their size, see Ramey (2019).

We formalize the fiscal policy intervention as an unanticipated expansionary disturbance $d_1 = \epsilon_1^d$ in period 1. Afterwards, the policy shock d_t follows the autoregressive process (3.52). Notice that the fiscal shock is expressed in real terms.

Perhaps the most frequently used concept is the *ex ante present-value* output multiplier defined for a particular time horizon. For time span between periods 1 and T, the ex ante value added multiplier m_T^{VA} is defined as

$$m_T^{VA} = \frac{\sum_{t=1}^{T} \beta^{t-1} \Delta VA_t}{\sum_{t=1}^{T} \beta^{t-1} d_t}, \tag{3.58}$$

where ΔVA_t denotes the deviation of value added in period t from the steady state, and β is the real discount factor. Alternatively to value added multipliers, GDP and consumption multipliers are also used to describe the economic effects of fiscal policies.

The second concept on which we focus is the *ex-post* present-value multiplier which takes into account the fact that all variables adjust in response to a government spending shock. Thus, the budgetary consequences of the shock differ from $d_t^{\times}$. For time horizon 1 to T, the ex post value added multiplier $\bar{m}_T^{VA}$ is defined as

$$\bar{m}_T^{VA} = \frac{\sum_{t=1}^{T} \beta^{t-1} \Delta VA_t}{\sum_{t=1}^{T} \beta^{t-1} \Delta B_t^G}, \tag{3.59}$$

where $\Delta B_t^G = B_t^G - B^G$ is the change in the government budget position in period t compared to the steady state. Typically, ΔB_t^G is smaller than $d_t^{\times}$ because an expansionary policy shock is partly self-financed by increased tax revenues. The self-financing ratio at horizon T is defined as

$$sf_T = 1 - \frac{\sum_{t=1}^{T} \beta^{t-1} \Delta B_t^G}{\sum_{t=1}^{T} \beta^{t-1} d_t^{\times}}. \tag{3.60}$$

Note that for a fully self-financed measure, the value of the ex post multipliers goes to infinity. Therefore, in the case of high self-financing, we often see big multipliers.

Aggregate output multipliers, permanent shock										
	impact	short run (1 year)			medium run (4 years)			long run (30 years)		
shock	m_1^{VA}	m_4^{VA}	$\bar{m}_4^{VA}$	sf_4	m_{16}^{VA}	$\bar{m}_{16}^{VA}$	sf_{16}	m_{120}^{VA}	$\bar{m}_{120}^{VA}$	sf_{120}
C^G	0.68	0.60	0.85	0.29	0.54	0.68	0.20	0.50	0.58	0.14
I^G	1.04	0.77	1.48	0.48	0.75	1.06	0.30	1.43	2.63	0.46
LST^K	0.34	0.21	0.27	0.21	0.12	0.13	0.10	0.06	0.06	0.03
LST^R	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	0.02
τ^C	0.50	0.37	0.51	0.28	0.30	0.36	0.18	0.31	0.35	0.13

Table 3.2: Aggregate output multipliers generated by a permanent shock to public consumption C^G, public investment I^G, transfers $LST^{K/R}$, and consumption tax rate τ^C.

Aggregate output multipliers, temporary shock										
	impact	short run (1 year)			medium run (4 years)			long run (30 years)		
shock	m_1^{VA}	m_4^{VA}	$\bar{m}_4^{VA}$	sf_4	m_{16}^{VA}	$\bar{m}_{16}^{VA}$	sf_{16}	m_{120}^{VA}	$\bar{m}_{120}^{VA}$	sf_{120}
C^G	0.78	0.67	1.14	0.42	0.55	0.77	0.29	0.40	0.46	0.12
I^G	0.61	0.52	0.73	0.28	0.70	0.97	0.28	1.44	3.07	0.53
LST^K	0.53	0.35	0.58	0.40	0.16	0.20	0.22	-0.05	-0.05	-0.05
LST^R	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.03	-0.03	0.03
τ^C	0.55	0.42	0.69	0.40	0.31	0.43	0.29	0.19	0.23	0.14

Table 3.3: Aggregate output multipliers generated by a temporary shock to public consumption C^G, public investment I^G, transfers $LST^{K/R}$, and consumption tax rate τ^C.

3.4.2 Aggregate multipliers

This section presents the multipliers generated by the model for a set of standard *aggregate* policy shocks. Using somewhat sloppy terminology, we refer to these as aggregate multipliers. Table 3.2 reports the aggregate output multipliers for a permanent change in public consumption, public investment, transfers, and the consumption tax rate implied by our model for various time horizons. All multipliers are well in line with the existing literature, in particular Schuster (2019) and de Walque et al. (2015).

With the exception of government investment, all multipliers lie between (close to) zero and one. Government investment generates the highest output effects for all time horizons, with ex post multipliers above one. This is a consequence of the assumption that public capital efficiently increases the overall productivity of the economy. Not surprisingly, Ricardian households react very weakly to the change in their lump sum transfers. The output effect of transfers to Keynesian households is also moderate, despite their high propensity to consume. Instead of domestic value added, imports increase considerably. Moreover, Ricardian households perceive transfers to Keynesians as negative shocks to their lifetime wealth and decrease their consumption, offsetting the positive demand effect, see Schuster (2019) for further discussion. All multipliers lie within the ranges that Schuster (2019) identifies by varying the parameter values and are very close to the multipliers generated by his benchmark calibration. The consumption tax rate in our model generates somewhat higher short-run multiplier compared to Schuster (2019), but is close in the long run.

For comparison, table 3.3 reports the same aggregate output multipliers as table 3.2, but for temporary policy shocks. Again, all values are well in line with the literature. The most striking difference to the permanent shocks is the lower short-run effect of government investment. A temporary shock to government investment only increases the stock of public capital by a

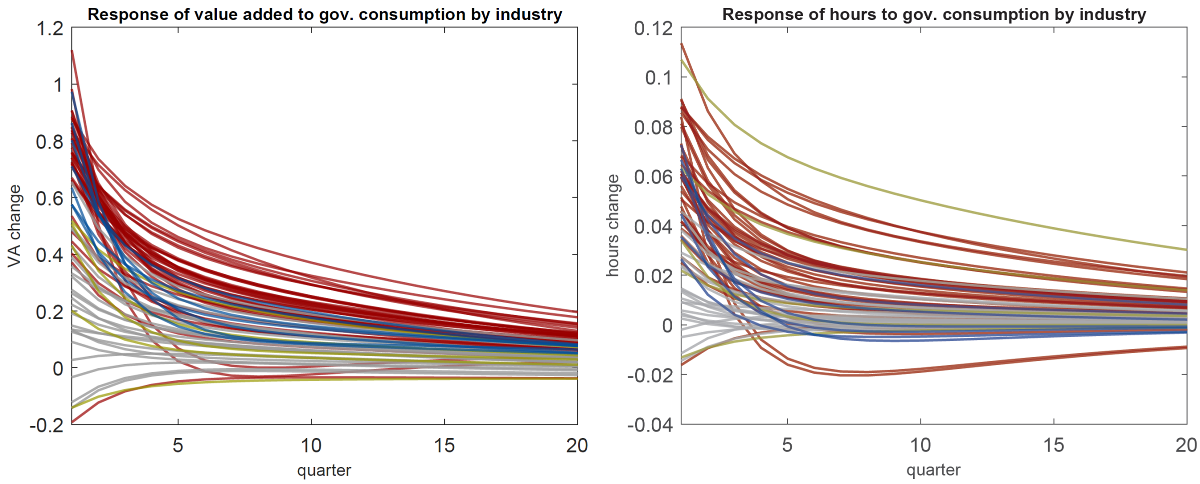

Figure 3.2: Variation in the responses of aggregate variables to government consumption shock in different industries. Responses of aggregate value added (left) and hours (right) to a transitory government consumption shock of size 1 in each of the 74 industries. Manufacturing industries (grey), services (red), construction and utilities (blue), mining and agriculture (yellow). Persistence parameter $\rho = 0.95$ (medium persistency).

small amount, generating a relatively small change in aggregate productivity in the medium and long run. Thus, the lifetime wealth of Ricardian households changes relatively little and so does their demand for consumption and investment goods on impact. Using the same logic, government consumption and transfers to Keynesian households generate stronger short-run responses compared to the permanent case, as they only decrease the lifetime wealth of Ricardian households by a small amount.

3.4.3 Industry-specific consumption multipliers

We now turn to examining the effects of government spending at the level of industries. Figure 3.2 plots the responses of aggregate value added and hours to a transitory government consumption shock of equal size in each of the 74 industries. The two key observations are:

- The model predicts a large heterogeneity in the response of output and hours to government consumption shocks in different industries.
- The responses of aggregate variables vary systematically depending on the sector of the economy, as revealed by the colour-coding of the impulse-response functions.

The heterogeneity in the responses of the aggregate variables also translates into a high variation of multiplier values. Tables 3.4 and 3.5 characterize the distribution of the multipliers across government consumption of goods of different industries. We refer to the multipliers that measure the aggregate response of the economy to a government consumption shock in a particular industry as the industry-specific government consumption multipliers.

The differences between the industry-specific multipliers implied by the model are dramatic. As figure 3.2 suggests, the highest multipliers are generated by spending in the service industries. After one year, the highest multipliers (both ex ante and ex post) are in *education services*; *public*

Industry-specific multipliers, permanent shock							
	impact	short run (1 year)		medium run (4 years)		long run (30 years)	
	m_1^{VA}	m_4^{VA}	$\bar{m}_4^{VA}$	m_{16}^{VA}	$\bar{m}_{16}^{VA}$	m_{120}^{VA}	$\bar{m}_{120}^{VA}$
Mean	0.49	0.39	0.58	0.30	0.36	0.20	0.21
Median	0.61	0.50	0.67	0.34	0.37	0.25	0.23
St. deviation	0.40	0.27	0.44	0.19	0.25	0.17	0.18
Variance	0.16	0.07	0.19	0.04	0.06	0.03	0.03

Table 3.4: Distribution across 74 industry-specific multipliers, permanent shock to government consumption in each of the industries.

Industry-specific multipliers, transitory shock							
	impact	short run (1 year)		medium run (4 years)		long run (30 years)	
	m_1^{VA}	m_4^{VA}	$\bar{m}_4^{VA}$	m_{16}^{VA}	$\bar{m}_{16}^{VA}$	m_{120}^{VA}	$\bar{m}_{120}^{VA}$
Mean	0.55	0.43	0.65	0.30	0.39	0.11	0.14
Median	0.61	0.44	0.60	0.29	0.33	0.10	0.09
St. deviation	0.24	0.21	0.41	0.19	0.29	0.22	0.24
Variance	0.06	0.04	0.17	0.04	0.09	0.05	0.06

Table 3.5: Distribution across 74 industry-specific multipliers, transitory shock to government consumption in each of the industries.

administration, defence, social security services; and *real estate services.* For permanent shocks, the values of 1-year ex ante output multipliers in these industries are around 0.75 and higher than one for the corresponding ex post multipliers. On the contrary, the lowest multipliers are in manufacturing industries *coke and refined petroleum products* and *wearing apparel*, mining industry *coal, crude petroleum and natural gas, metal ores* and in *water transport* service industry. In these industries, output multipliers have negative values. Table 3.15 in Appendix 3.A lists the values of the multipliers for all industries.

The large differences between the multipliers across industries are obviously interesting from the policy perspective. The ex post multipliers reveal that various government spending interventions with the same budgetary consequences vary in their ability to stimulate the economy. Moreover, the sensitivity of the spending multipliers with respect to the industry characteristics might to some extent explain the large variation of the existing empirical estimates. In the next section, we turn to examining the sources of the heterogeneity across the industry-specific multipliers.

3.5 Sources of heterogeneity

The industries in the model differ along a number of dimensions which may influence the sizes of the industry-specific multipliers. In this section, we list these industry characteristics and analyse their contribution to the overall heterogeneity across multipliers. We use the standard deviations across industry multipliers from table 3.4 as our measure of heterogeneity.

For illustration, figures 3.3 and 3.4 plot the industry-specific multipliers implied by the model against various industry characteristics. Since we have used these industry characteristics to calibrate the model industries, they are the same in the data and the model (steady state). We see that some of the characteristics, especially the import shares, production factor shares (labor and intermediate input shares), and to a lesser extent also use shares of the industry output

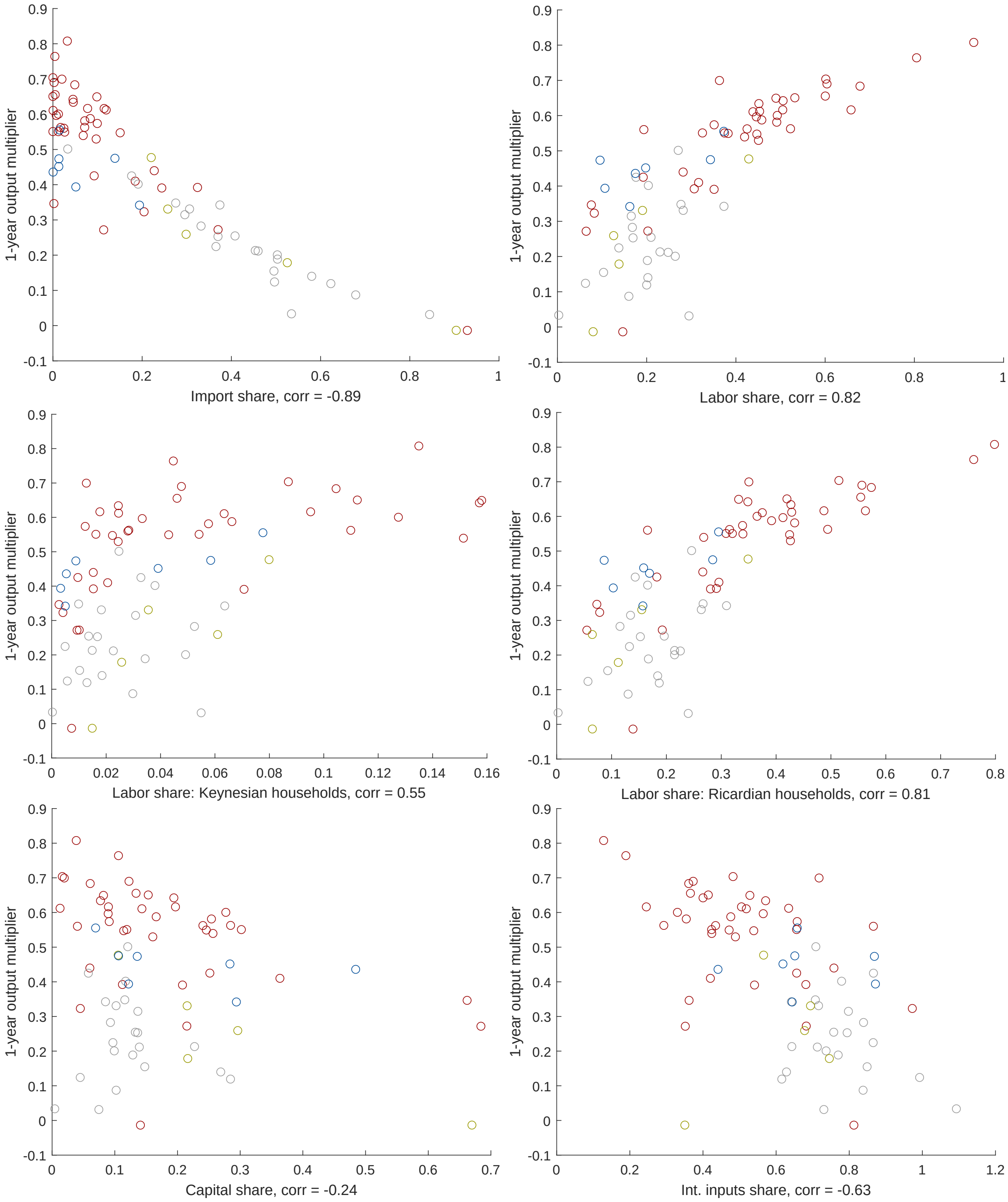

Figure 3.3: Output multipliers and industry characteristics. One-year industry-specific value added multipliers, temporary shock to government consumption in each of the 74 industries; production factor shares and import share. Manufacturing industries (grey), services (red), construction and utilities (blue), mining and agriculture (yellow).

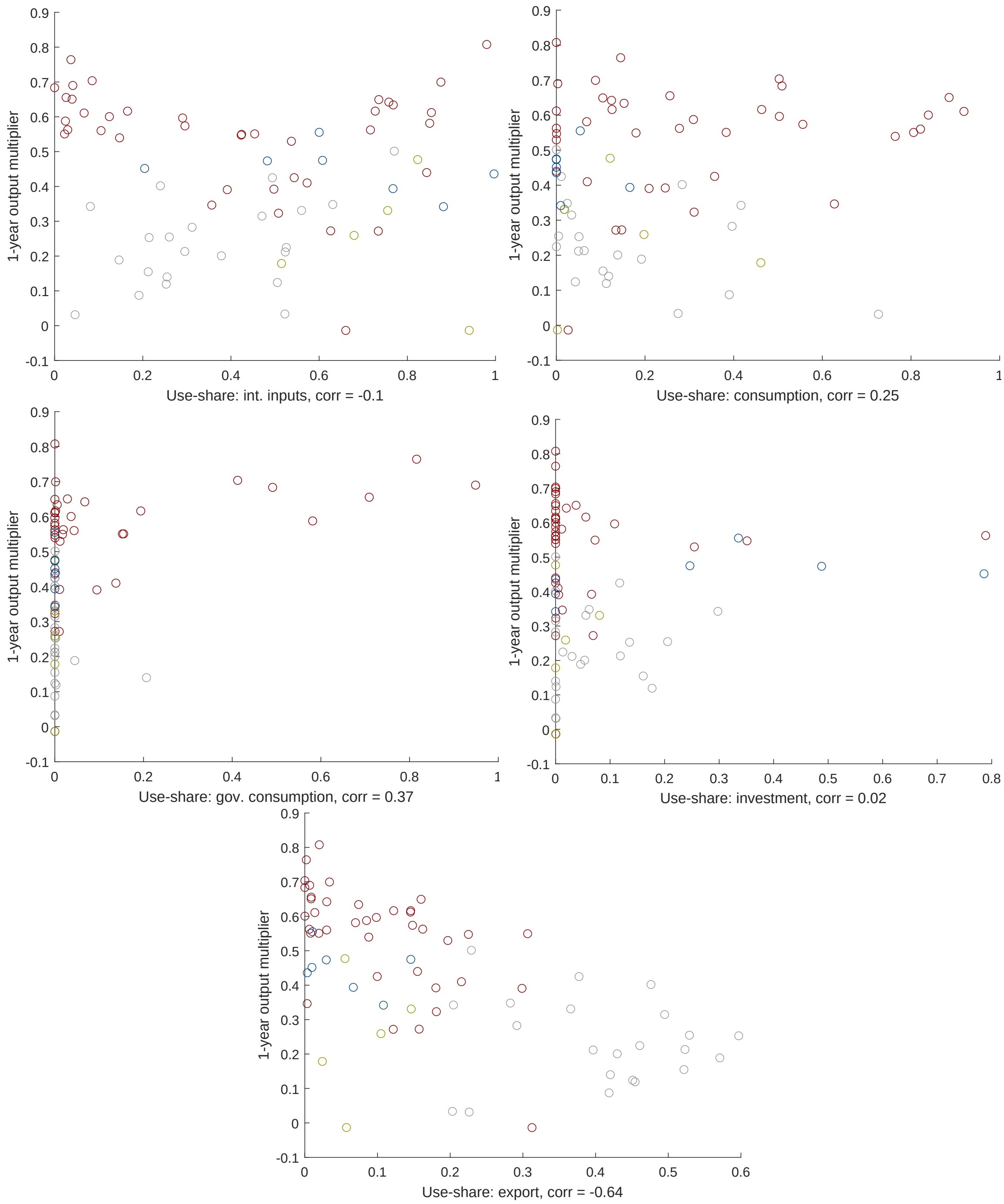

Figure 3.4: Output multipliers and industry characteristics. One-year industry-specific value added multipliers, temporary shock to government consumption in each of the 74 industries; use shares. Manufacturing industries (grey), services (red), construction and utilities (blue), mining and agriculture (yellow).

Alternative calibrations: equal industry shares - permanent shock							
	impact	short run (1 year)		medium run (4 years)		long run (30 years)	
	m_1^{VA}	m_4^{VA}	$\bar{m}_4^{VA}$	m_{16}^{VA}	$\bar{m}_{16}^{VA}$	m_{120}^{VA}	$\bar{m}_{120}^{VA}$
Benchmark	*0.40*	*0.27*	*0.44*	*0.19*	*0.25*	*0.17*	*0.18*
Import share	0.21	0.16	0.17	0.23	0.27	0.17	0.20
Production factor shares	0.87	0.86	1.02	0.77	0.75	0.71	0.72
Capital share	0.91	0.96	0.99	0.95	0.93	0.90	0.90
Int. inputs share	0.81	0.81	0.89	0.81	0.84	0.73	0.76
Labor share	1.06	0.96	1.36	0.80	0.76	0.81	0.78
Rel. labor share K/R	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Input-output structure	0.85	0.80	9.62	0.75	0.83	0.59	0.65
Use share consumption	0.96	0.98	0.92	1.01	1.00	1.00	1.02
Use share gov. consumption	0.99	0.98	0.79	0.94	0.90	0.90	0.89
Use share investment	1.01	1.02	1.10	1.01	1.01	0.99	0.97
Use share exports	0.93	0.92	4.43	0.92	1.03	0.85	0.92
Symmetric case	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 3.6: Standard deviation of multiplier values, relative to benchmark (for all rows except of benchmark). Each row represents alternative calibration, keeping the selected industry characteristic same across industries. Output multipliers, permanent shock.

correlate with the multipliers. Figures 3.3 and 3.4 indicate there are some relationships between the multipliers and industry characteristics, but they do not reveal which characteristics actually cause the variation across the multipliers.

Therefore, we turn to the main exercise of this paper, in which we recalibrate the model several times, each time shutting down one potential source of the heterogeneity. Tables 3.6 and 3.7 show the results of the main exercise. The tables plot standard deviations of the multiplier values across industries, relative to benchmark (for all rows except of benchmark). Each row represents one alternative calibration of the model, where a selected industry characteristic is set to be the same across all industries. Appendix 3.A reports additional information for the alternative model calibrations, including the mean and median across industries.

Before discussing the results, a clarifying note is necessary. Because of the market clearing conditions, it is not possible to alter one of the industry characteristics in the model and keep all the others unchanged. Thus, we have conducted the exercise in the following way: in each of the alternative calibrations, we have changed the values of one *parameter* such that it generates the same values for one selected industry characteristic (for example, we set export weights ν_i^{EXPT} such that the export use share in all industries is the same). The values are set such that the aggregate quantities stay unchanged (e.g. the aggregate export share is the same as in the benchmark calibration). The rest of the parameters are kept the same as in the benchmark calibration. For each of the alternative calibrations, we solve the model to find the new equilibrium and compute the multipliers. In some cases, other industry characteristics are influenced by the recalibration. However, we find that in all cases, such unintended changes are small compared to the intended change in the selected characteristic and can be ignored.

Tables 3.6 and 3.7 show that for the use shares, i.e. the shares of the industry output used on private and government consumption, investment, and exports, the relative standard deviations of multiplier values across industries are very close to one. Thus, the use shares do not significantly influence the heterogeneity across the multipliers at any time horizon. Import share, production

Alternative calibrations: equal industry shares - temporary shock							
	impact	short run (1 year)		medium run (4 years)		long run (30 years)	
	m_1^{VA}	m_4^{VA}	$\bar{m}_4^{VA}$	m_{16}^{VA}	$\bar{m}_{16}^{VA}$	m_{120}^{VA}	$\bar{m}_{120}^{VA}$
Benchmark	*0.24*	*0.21*	*0.41*	*0.19*	*0.29*	*0.22*	*0.24*
Import share	0.27	0.40	0.38	0.54	0.50	0.52	0.50
Production factor shares	0.84	0.75	0.70	0.60	0.52	0.48	0.44
Capital share	0.97	0.95	0.90	0.87	0.80	0.79	0.75
Int. inputs share	0.85	0.87	0.88	0.88	0.87	0.81	0.83
Labor share	0.88	0.76	0.71	0.64	0.58	0.58	0.55
Rel. labor share K/R	0.99	1.00	0.98	1.00	1.00	0.99	1.00
Input-output structure	0.88	0.87	1.18	0.85	0.88	0.73	0.80
Use share consumption	0.99	1.00	0.94	1.00	1.00	0.99	1.01
Use share gov. consumption	0.99	0.98	0.85	0.96	0.95	0.93	0.94
Use share investment	1.00	0.99	0.99	0.97	0.96	0.95	0.92
Use share exports	0.98	0.98	1.47	0.96	0.99	0.87	0.95
Symmetric case	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 3.7: Standard deviation of multiplier values, relative to benchmark (for all rows except of benchmark). Each row represents alternative calibration, keeping the selected industry characteristic same across industries. Output multipliers, temporary shock.

factor shares and the input-output structure of the economy, on the other hand, contribute to the heterogeneity.

According to the model, the variation in import shares across industries is the most important driver of the heterogeneity across multipliers. This finding is very intuitive. If the government spends resources on goods that were produced abroad, the resources leave the domestic economy and are lost for the labor and capital owners at home. Thus, spending resources in the industries with low import shares, i.e. services, utilities, and construction generates higher multipliers. However, the quantitative importance of the import shares is quite striking. For temporary shocks, recalibrating the model with the same import share in all industries decreases the volatility of the multipliers by about 60% in short run and about 45% in the medium run. In the case of permanent shocks, the changes are even bigger - the volatility decreases by 84% in the short run and by 77% in the medium run.

The variation in cost shares of production factors also turns out to be important for the value of multipliers across industries, especially in the medium and long run. Intermediate inputs share and labor share turn out to be more important compared to the capital share. A high share of intermediate inputs has a twofold negative effect on the value of multipliers. First, unlike labor, part of the intermediate inputs is imported from abroad. This effect is present already on impact. Second, higher demand for intermediate goods creates upward pressure on the prices of intermediate goods for all industries. Over time, as firms are able to adjust prices, the effect of high intermediate input shares increases in the case of permanent shock. High labor share mirrors the two channels mentioned above, with an additional effect of the resources going directly to the Keynesian households. Keynesian households drive the demand up due to their high propensity to consume. However, the latter effect again appears with a delay, once the firms are able to adjust their prices and increase the demand for labor. Thus, the contribution of labor share in generating the heterogeneity increases in the medium run.

The rich strand of literature starting with Horvath (2000) has found that shocks to industries which act as intermediate inputs suppliers impact aggregate variables more strongly than other industries. Our result is consistent with these findings. We recalibrate the model such that the input-output table becomes completely symmetric, i.e. industries supply the same share of their output as intermediate inputs and the composition of intermediate inputs supplied to each industry is the same. With the symmetric input-output network, the volatility of the multipliers decreases substantially, especially in the case of a permanent shock. In the asymmetric case, the government consumption in the industries which serve as intermediate input suppliers increases the price of inputs for all industries, causing crowding out and decreasing the multipliers.

Lastly, we find that the differences in the relative share of Keynesian and Ricardian workers across industries do not affect the heterogeneity, although the two types of households have different propensity to consume. The reason for this is a combination of two facts. First, the share of resources that goes directly to labor in the particular industry is small, considering import shares, intermediate input shares, and capital. Second, the industry differences in the relative share of Keynesian households that we have identified from the SILC data are moderate. Moreover, Ricardian households view a shift of resources to Keynesian households as a loss and react to it with a decreased demand.

To summarize the findings, the government generates more output growth by consuming goods that are likely to be produced at home, do not serve as intermediate inputs to other industries, and are produced using high labor share and low intermediate inputs share. This characterization is most common between service industries, but can also be found in other sectors, for example *buildings and building construction works* and *natural water, water treatment and supply services*.

3.6 Government investment

The second major type of government spending is public investment. We now turn our attention to the implications of the model for spending on various types of investment. Table 3.8 reports the aggregate output multipliers for the permanent shock to five different types of investment, using the classification of the Austrian IOT.

The first observation is that there are big differences between the investment types predicted by the model, especially in the short run. In the long run, government investment increases the productivity of the economy as a whole, leading to increased output and wealth of the agents. This positive outlook about the future productivity also influences the multipliers in the short run. Ricardian households take into account the future gains from the increased productivity, which dampens the crowding out effect of the government spending. However, the factors discussed in section 3.5 turn out to be more important in the short run. Since *machinery* and *transport equipment* investment consist of the industry goods with high import share, low labor share and high intermediate input shares, they generate relatively low multipliers. On the other hand construction and intangible investment (consisting mainly from R&D and professional services) have comparatively high labor share and low import shares.

Table 3.8 also shows that government investment is not an universally better fiscal stimulus than government consumption. Even though our model is quite optimistic about the effect of public investment on future productivity, in the short run investment in machinery and transport

Output multipliers: government investment by type, permanent shock										
	impact	short run (1 year)			medium run (4 years)			long run (30 years)		
shock	m_1^{VA}	m_4^{VA}	$\bar{m}_4^{VA}$	sf_4	m_{16}^{VA}	$\bar{m}_{16}^{VA}$	sf_{16}	m_{120}^{VA}	$\bar{m}_{120}^{VA}$	sf_{120}
Dwellings	1.32	0.90	2.15	0.58	0.67	0.93	0.28	1.27	1.94	0.35
Other construction	1.31	0.90	2.10	0.57	0.68	0.94	0.28	1.29	2.02	0.36
Machinery	0.57	0.50	0.68	0.27	0.67	0.89	0.24	1.46	2.81	0.48
Transport equipment	0.44	0.42	0.53	0.21	0.68	0.89	0.23	1.49	2.95	0.49
Intangible and other	1.24	0.96	2.53	0.62	0.99	1.76	0.44	1.67	4.43	0.62

Table 3.8: Aggregate output multipliers after a permanent shock to each type of investment.

Output multipliers: government investment by type, temporary shock										
	impact	short run (1 year)			medium run (4 years)			long run (30 years)		
shock	m_1^{VA}	m_4^{VA}	$\bar{m}_4^{VA}$	sf_4	m_{16}^{VA}	$\bar{m}_{16}^{VA}$	sf_{16}	m_{120}^{VA}	$\bar{m}_{120}^{VA}$	sf_{120}
Dwellings	0.69	0.52	0.75	0.30	0.49	0.62	0.21	1.35	2.44	0.45
Other construction	0.69	0.53	0.75	0.30	0.51	0.64	0.21	1.36	2.54	0.46
Machinery	0.44	0.43	0.55	0.21	0.77	1.07	0.28	1.44	2.95	0.51
Transport equipment	0.36	0.38	0.47	0.17	0.82	1.14	0.28	1.47	2.92	0.50
Intangible and other	0.74	0.68	1.09	0.38	0.97	1.68	0.42	1.59	5.70	0.72

Table 3.9: Aggregate output multipliers after a temporary shock to each type of investment.

equipment generates smaller ex-ante and ex-post multipliers than government consumption in some industries.

The case is even stronger when we consider temporary policy shocks, which we report in table 3.9. The government investment multipliers are even smaller in short and medium run, see the discussion in section 3.4.2. Investment into intangible capital is the only case which generates effects comparable with the high end of the government consumption multipliers. All other types of investment generate short run effects that are smaller compared to government consumption for most of the service industries.

3.7 Conclusions

In this paper, we study the fiscal multipliers in a small open economy from the perspective of an industry-level New Keynesian model. We focus on the heterogeneity of multipliers for government spending across industries, and across types of government investment. We show that a disaggregated New Keynesian model calibrated to reflect Austria predicts a very high heterogeneity of multipliers for government spending across the 74 individual industries. Moreover, we show that the government investment multipliers vary across the types of capital.

We identify the industry characteristics that drive the differences in spending multipliers in the model economy. We show that the major sources of heterogeneity across multipliers are (1) differences in import shares across industries, (2) production factor shares (especially labor share and intermediate input share) and (3) asymmetry of the input-output network. The relative importance of these factors differ depending on the type of multiplier, considered time horizon, and persistence of the policy. However, industry import share is the most important determinant for all cases that we consider in this paper. On the contrary, the differences in the way how industry output is used and composition of labor force across industries appear to have only minor effects on the values of the multipliers.

Interestingly, our model questions the notion that governments should stimulate the economy by investing into infrastructure projects in bad times. In our model, the temporary government investment shocks (with the exception of the intangible investments, such as R&D) generate lower short run multipliers compared to government consumption in a number of service industries. Even though from a long-term perspective, investment is favourable due to its positive effects on aggregate productivity, it takes time before these effects materialize. In the short run, government investment spending is more import-intensive, more likely to crowd out investment and intermediate inputs from the private sector and less likely to increase the income of credit-constrained households, all of which mitigates its expansionary effects.

Our finding that the import intensity is the major factor determining the multipliers is clearly only valid in the case of a small open economy. The multipliers would look differently if we computed them from a global perspective, in our case for the whole monetary union that contains Austria and the rest of the world. Such "global" multipliers would not be affected by the import shares, and the effects of the government investment would increase, especially in the short run. Thus, synchronization and evaluation of fiscal interventions at the level of the monetary union could change the ranking of the policy shocks and lead to efficiency improvements in both short and long run.

Appendix 3

3.A Industry multipliers

Robustness: multipliers with alternative parameter values							
	Baseline	$\sigma_l = 20$	$\sigma_N = 0.5$	$\eta = 1$	$\omega = 0.5$	$\kappa = 4$	$\sigma_k = 0.5$
Aggregate multiplier	0.60	0.60	0.75	0.70	0.60	0.57	0.61
Mean industry multiplier	0.39	0.38	0.38	0.43	0.38	0.36	0.40
Median industry multiplier	0.50	0.50	0.47	0.53	0.47	0.42	0.51
St. deviation industry multiplier	0.27	0.27	0.27	0.30	0.23	0.24	0.28

Table 3.10: Robustness. Output multipliers m_4^{VA}, shocks to government consumption (aggregate and industry). Results for alternative parameter values.

Alternative calibrations: equal industry shares - permanent shock (mean)							
	impact	short run (1 year)		medium run (4 years)		long run (30 years)	
	m_1^{VA}	m_4^{VA}	$\bar{m}_4^{VA}$	m_{16}^{VA}	$\bar{m}_{16}^{VA}$	m_{120}^{VA}	$\bar{m}_{120}^{VA}$
Benchmark	0.49	0.39	0.58	0.30	0.36	0.20	0.21
Import share	0.51	0.40	0.48	0.32	0.36	0.27	0.26
Prod. factor shares	0.59	0.43	0.70	0.32	0.38	0.28	0.27
Capital share	0.56	0.42	0.63	0.32	0.37	0.24	0.24
Int. inputs share	0.52	0.39	0.61	0.31	0.37	0.24	0.24
Labor share	0.55	0.42	0.72	0.31	0.37	0.25	0.24
Rel. labor share K/R	0.50	0.39	0.58	0.30	0.37	0.20	0.21
Input-output structure	0.57	0.43	0.42	0.32	0.39	0.27	0.26
Use share consumption	0.53	0.41	0.58	0.32	0.38	0.23	0.24
Use share gov. consumption	0.50	0.39	0.49	0.30	0.35	0.21	0.21
Use share investment	0.50	0.40	0.63	0.31	0.37	0.20	0.21
Use share exports	0.50	0.39	0.78	0.31	0.40	0.26	0.26
Symmetric case	0.58	0.44	0.56	0.35	0.38	0.33	0.31

Table 3.11: Mean multiplier values. Each row represents alternative calibration, keeping the selected industry characteristic same across industries. Output multipliers, permanent shock.

Alternative calibrations: equal industry shares - permanent shock (median)							
	impact	short run (1 year)		medium run (4 years)		long run (30 years)	
	m_1^{VA}	m_4^{VA}	$\bar{m}_4^{VA}$	m_{16}^{VA}	$\bar{m}_{16}^{VA}$	m_{120}^{VA}	$\bar{m}_{120}^{VA}$
Benchmark	0.61	0.50	0.67	0.34	0.37	0.25	0.23
Import share	0.50	0.40	0.47	0.32	0.35	0.27	0.25
Prod. factor shares	0.75	0.55	0.83	0.39	0.46	0.33	0.31
Capital share	0.71	0.52	0.71	0.37	0.41	0.30	0.28
Int. inputs share	0.63	0.50	0.73	0.35	0.38	0.28	0.26
Labor share	0.64	0.51	0.71	0.39	0.44	0.29	0.28
Rel. labor share K/R	0.62	0.50	0.68	0.34	0.38	0.25	0.24
Input-output structure	0.67	0.50	0.82	0.35	0.41	0.30	0.28
Use share consumption	0.64	0.52	0.67	0.36	0.39	0.29	0.28
Use share gov. consumption	0.61	0.50	0.58	0.35	0.37	0.27	0.26
Use share investment	0.63	0.50	0.68	0.35	0.38	0.27	0.25
Use share exports	0.61	0.49	0.78	0.35	0.41	0.30	0.29
Symmetric case	0.58	0.44	0.56	0.35	0.38	0.33	0.31

Table 3.12: Median multiplier values. Each row represents alternative calibration, keeping the selected industry characteristic same across industries. Output multipliers, permanent shock.

Alternative calibrations: equal industry shares - temporary shock (mean)							
	impact	short run (1 year)		medium run (4 years)		long run (30 years)	
	m_1^{VA}	m_4^{VA}	$\bar{m}_4^{VA}$	m_{16}^{VA}	$\bar{m}_{16}^{VA}$	m_{120}^{VA}	$\bar{m}_{120}^{VA}$
Benchmark	0.55	0.43	0.65	0.30	0.39	0.11	0.14
Import share	0.53	0.42	0.54	0.31	0.36	0.19	0.18
Prod. factor shares	0.56	0.43	0.64	0.30	0.35	0.20	0.18
Capital share	0.55	0.43	0.65	0.30	0.37	0.15	0.16
Int. inputs share	0.54	0.41	0.63	0.29	0.37	0.15	0.16
Labor share	0.56	0.43	0.66	0.30	0.36	0.17	0.16
Rel. labor share K/R	0.55	0.43	0.65	0.30	0.39	0.12	0.15
Input-output structure	0.59	0.45	0.82	0.30	0.39	0.19	0.20
Use share consumption	0.55	0.43	0.63	0.31	0.40	0.14	0.17
Use share gov. consumption	0.55	0.43	0.59	0.30	0.38	0.14	0.16
Use share investment	0.55	0.43	0.66	0.29	0.38	0.09	0.12
Use share exports	0.54	0.42	0.84	0.30	0.40	0.18	0.20
Symmetric case	0.55	0.43	0.56	0.31	0.35	0.25	0.22

Table 3.13: Mean multiplier values. Each row represents alternative calibration, keeping the selected industry characteristic same across industries. Output multipliers, temporary shock.

Alternative calibrations: equal industry shares - temporary shock (median)							
	impact	short run (1 year)		medium run (4 years)		long run (30 years)	
	m_1^{VA}	m_4^{VA}	$\bar{m}_4^{VA}$	m_{16}^{VA}	$\bar{m}_{16}^{VA}$	m_{120}^{VA}	$\bar{m}_{120}^{VA}$
Benchmark	0.61	0.44	0.60	0.29	0.33	0.10	0.09
Import share	0.52	0.41	0.52	0.31	0.36	0.19	0.17
Prod. factor shares	0.66	0.50	0.72	0.33	0.39	0.22	0.19
Capital share	0.62	0.47	0.64	0.32	0.36	0.16	0.14
Int. inputs share	0.60	0.42	0.59	0.29	0.33	0.16	0.14
Labor share	0.66	0.49	0.73	0.32	0.37	0.18	0.16
Rel. labor share K/R	0.61	0.44	0.60	0.29	0.33	0.11	0.09
Input-output structure	0.66	0.46	0.80	0.31	0.37	0.19	0.17
Use share consumption	0.60	0.44	0.57	0.31	0.34	0.13	0.11
Use share gov. consumption	0.61	0.44	0.54	0.30	0.33	0.13	0.11
Use share investment	0.62	0.44	0.62	0.30	0.34	0.10	0.08
Use share exports	0.60	0.43	0.75	0.30	0.34	0.18	0.15
Symmetric case	0.55	0.43	0.56	0.31	0.35	0.25	0.22

Table 3.14: Mean multiplier values. Each row represents alternative calibration, keeping the selected industry characteristic same across industries. Output multipliers, temporary shock.

Value added multipliers - government consumption by industry													
		permanent shock						temporary shock					
		short run (1 year)			medium run (4 years)			short run (1 year)			medium run (4 years)		
Industry	Sector	m_4^X	$\bar{m}_4^X$	sf_4	m_{16}^X	$\bar{m}_{16}^X$	sf_{16}	m_4^X	$\bar{m}_4^X$	sf_4	m_{16}^X	$\bar{m}_{16}^X$	sf_{16}
Real estate services	S	0.73	1.44	0.49	0.36	0.38	0.04	0.35	0.46	0.25	0.04	0.04	-0.03
Services of households, dom. personnel	S	0.71	1.35	0.47	0.56	0.86	0.34	0.87	2.07	0.58	0.73	1.32	0.45
Education services	S	0.75	1.30	0.42	0.65	0.92	0.29	0.76	1.45	0.47	0.67	1.04	0.36
Public administration, defence, soc. security	S	0.73	1.26	0.42	0.61	0.82	0.26	0.69	1.23	0.44	0.57	0.83	0.31
Other personal services	S	0.67	1.17	0.43	0.45	0.56	0.19	0.60	1.00	0.40	0.40	0.51	0.22
Retail trade, exc. o.motor vehicles a. -cycles	S	0.67	1.16	0.42	0.48	0.62	0.22	0.65	1.13	0.42	0.48	0.64	0.26
Employment services	S	0.70	1.15	0.39	0.57	0.80	0.30	0.81	1.61	0.50	0.68	1.12	0.39
Natural water; water treatment and supply services	C	0.67	1.13	0.41	0.39	0.43	0.08	0.44	0.61	0.28	0.20	0.21	0.06
Sporting services, amusement and recreation services	S	0.66	1.12	0.41	0.44	0.53	0.17	0.55	0.87	0.36	0.36	0.43	0.18
Gambling and betting services	S	0.62	1.09	0.44	0.46	0.62	0.26	0.61	1.11	0.45	0.46	0.66	0.31
Human health services	S	0.65	1.08	0.39	0.54	0.73	0.25	0.66	1.15	0.43	0.54	0.77	0.30
Services furnished by membership organisations	S	0.63	1.06	0.40	0.53	0.77	0.30	0.70	1.36	0.48	0.60	0.96	0.38
Other business support services	S	0.65	1.05	0.38	0.47	0.59	0.19	0.64	1.08	0.40	0.47	0.62	0.24
Scientific research and development services	S	0.65	1.04	0.37	0.46	0.55	0.18	0.56	0.87	0.36	0.37	0.46	0.19
Rental and leasing services	S	0.61	1.01	0.39	0.29	0.28	-0.02	0.27	0.34	0.20	-0.02	-0.02	-0.08
Legal and accounting services	S	0.63	0.99	0.36	0.44	0.53	0.17	0.58	0.92	0.36	0.41	0.51	0.20
Residential care services, social work services	S	0.62	0.97	0.36	0.52	0.69	0.25	0.68	1.22	0.44	0.57	0.84	0.32
Wholesale trade, exc. o.motor vehicles a. -cycles	S	0.62	0.96	0.35	0.44	0.52	0.16	0.55	0.84	0.34	0.37	0.46	0.18
Services auxiliary to financial a. insurance services	S	0.61	0.95	0.36	0.51	0.71	0.28	0.70	1.25	0.44	0.60	0.91	0.35
Repair services of computers, pers. a. household goods	S	0.61	0.95	0.36	0.42	0.50	0.15	0.56	0.87	0.36	0.38	0.47	0.19
Buildings and building construction works	C	0.62	0.93	0.33	0.39	0.42	0.09	0.45	0.61	0.26	0.24	0.27	0.08
Accommod. services; food a.beverage serving services	S	0.58	0.89	0.35	0.39	0.46	0.15	0.54	0.84	0.36	0.36	0.44	0.18
Library, archive, museum and other cultural services	S	0.60	0.88	0.32	0.47	0.56	0.17	0.59	0.91	0.36	0.45	0.57	0.21
Creative, arts and entertainment services	S	0.58	0.86	0.33	0.45	0.55	0.19	0.62	1.01	0.39	0.47	0.63	0.25
Constructions a.construction works for civil engineering	C	0.59	0.84	0.30	0.40	0.45	0.10	0.47	0.64	0.26	0.30	0.33	0.11
Other prof., scientific, technical serv.; veterinary services	S	0.58	0.84	0.31	0.47	0.59	0.21	0.63	1.03	0.38	0.51	0.70	0.27
Financial services	S	0.55	0.83	0.33	0.45	0.59	0.24	0.62	1.04	0.41	0.50	0.72	0.30
Postal and courier services	S	0.57	0.82	0.31	0.46	0.57	0.20	0.65	1.08	0.40	0.52	0.71	0.27
Architectural and engineering services	S	0.57	0.81	0.29	0.41	0.48	0.14	0.53	0.77	0.31	0.37	0.46	0.18
Wholesale- a. retail trade, repair of motor vehicles	S	0.55	0.79	0.30	0.44	0.54	0.19	0.60	0.94	0.36	0.47	0.61	0.24
Travel agency, tour operator and related services	S	0.54	0.77	0.30	0.42	0.50	0.16	0.56	0.85	0.34	0.42	0.53	0.20
Specialised construction works	C	0.55	0.76	0.28	0.41	0.49	0.16	0.56	0.82	0.32	0.41	0.52	0.20
Programming and broadcasting services	S	0.54	0.75	0.28	0.42	0.49	0.15	0.55	0.82	0.33	0.41	0.51	0.19
Insurance, reinsurance and pension funding services	S	0.51	0.74	0.31	0.42	0.53	0.21	0.57	0.93	0.38	0.46	0.63	0.27
Telecommunications services	S	0.51	0.70	0.27	0.34	0.37	0.07	0.43	0.57	0.26	0.25	0.27	0.09
Serv. of head offices; management consulting services	S	0.51	0.69	0.26	0.44	0.54	0.19	0.61	0.96	0.36	0.51	0.69	0.26
Information technology serv., communication services	S	0.50	0.67	0.25	0.40	0.48	0.15	0.55	0.81	0.32	0.42	0.52	0.20

Value added multipliers - government consumption by industry - contd.

		permanent shock						temporary shock					
		short run (1 year)			medium run (4 years)			short run (1 year)			medium run (4 years)		
Industry	Sector	m_4^X	$\bar{m}_4^X$	sf_4	m_{16}^X	$\bar{m}_{16}^X$	sf_{16}	m_4^X	$\bar{m}_4^X$	sf_4	m_{16}^X	$\bar{m}_{16}^X$	sf_{16}
Warehousing and support services for transportation	S	0.49	0.67	0.27	0.33	0.35	0.07	0.41	0.55	0.26	0.23	0.25	0.08
Printing and recording services	M	0.48	0.62	0.23	0.38	0.43	0.12	0.50	0.70	0.29	0.37	0.44	0.16
Sewerage, waste management a. remediation services	C	0.41	0.52	0.21	0.27	0.28	0.04	0.34	0.43	0.21	0.17	0.18	0.05
Repair a.installation services of machinery a.equipment	C	0.42	0.52	0.19	0.34	0.38	0.10	0.47	0.65	0.27	0.35	0.41	0.15
Electricity, gas, steam and air conditioning	C	0.40	0.47	0.16	0.31	0.32	0.05	0.39	0.50	0.21	0.26	0.28	0.07
Products of forestry, logging and related services	P	0.38	0.45	0.17	0.31	0.34	0.10	0.48	0.67	0.28	0.36	0.44	0.17
Land transport services a. transport services via pipelines	S	0.36	0.44	0.18	0.27	0.29	0.07	0.39	0.52	0.25	0.26	0.29	0.11
Wood and products of wood and cork	M	0.35	0.41	0.13	0.30	0.32	0.07	0.42	0.55	0.23	0.32	0.36	0.12
Advertising and market research services	S	0.34	0.39	0.14	0.30	0.33	0.09	0.44	0.59	0.25	0.34	0.40	0.15
Beverages, Tobacco products	M	0.34	0.39	0.14	0.28	0.30	0.06	0.40	0.52	0.23	0.29	0.32	0.11
Other mining a. quarrying prod.; mining support services	P	0.33	0.38	0.14	0.23	0.24	0.03	0.33	0.41	0.20	0.19	0.20	0.06
Publishing activities	S	0.30	0.33	0.11	0.25	0.27	0.06	0.39	0.50	0.22	0.29	0.32	0.11
Other non-metallic mineral products	M	0.28	0.31	0.09	0.23	0.24	0.04	0.35	0.43	0.20	0.24	0.26	0.08
Air transport services	S	0.25	0.27	0.07	0.22	0.22	0.01	0.32	0.39	0.17	0.22	0.23	0.05
Products of agriculture, hunting and related services	P	0.24	0.27	0.09	0.16	0.16	-0.02	0.26	0.31	0.15	0.12	0.12	0.00
Paper and paper products	M	0.24	0.25	0.06	0.20	0.20	0.01	0.31	0.38	0.17	0.21	0.22	0.05
Fabricated metal products, exc. machinery and equipment	M	0.22	0.23	0.05	0.21	0.21	0.02	0.33	0.40	0.18	0.24	0.26	0.08
Audiovisual services	S	0.21	0.22	0.05	0.16	0.16	-0.01	0.27	0.32	0.15	0.16	0.16	0.03
Furniture	M	0.21	0.22	0.04	0.19	0.20	0.03	0.34	0.42	0.19	0.25	0.27	0.09
Food products	M	0.18	0.18	0.02	0.16	0.16	-0.01	0.28	0.33	0.15	0.18	0.19	0.04
Other transport equipment	M	0.14	0.14	-0.01	0.14	0.14	-0.02	0.25	0.29	0.13	0.16	0.17	0.02
Machinery and equipment n.e.c.	M	0.13	0.13	-0.01	0.14	0.13	-0.02	0.25	0.29	0.13	0.17	0.17	0.03
Electrical equipment	M	0.10	0.10	-0.03	0.10	0.10	-0.05	0.21	0.24	0.11	0.12	0.12	0.00
Basic metals	M	0.10	0.09	-0.04	0.11	0.11	-0.04	0.22	0.25	0.11	0.14	0.15	0.01
Rubber and plastic products	M	0.07	0.06	-0.06	0.09	0.09	-0.05	0.21	0.24	0.11	0.13	0.13	0.01
Fish and fishing products	P	0.06	0.06	-0.04	0.06	0.06	-0.06	0.18	0.20	0.10	0.09	0.09	-0.01
Other manufactured goods	M	0.03	0.03	-0.08	0.07	0.06	-0.06	0.19	0.21	0.10	0.12	0.12	0.00
Textiles	M	0.02	0.02	-0.09	0.07	0.06	-0.05	0.20	0.22	0.10	0.13	0.13	0.01
Motor vehicles, trailers and semi-trailers	M	0.01	0.01	-0.10	0.04	0.04	-0.08	0.15	0.17	0.07	0.08	0.08	-0.03
Basic pharmaceutical products and preparations	M	0.00	0.00	-0.10	0.03	0.03	-0.09	0.14	0.15	0.07	0.06	0.06	-0.04
Computer, electronic and optical products	M	-0.03	-0.03	-0.12	0.00	0.00	-0.10	0.12	0.13	0.06	0.04	0.04	-0.04
Chemicals and chemical products	M	-0.07	-0.06	-0.16	0.00	0.00	-0.10	0.12	0.13	0.04	0.07	0.07	-0.04
Leather and related products	M	-0.13	-0.11	-0.19	-0.04	-0.04	-0.12	0.09	0.09	0.03	0.04	0.03	-0.05
Coke and refined petroleum products	M	-0.20	-0.16	-0.25	-0.09	-0.08	-0.15	0.03	0.03	-0.01	-0.00	-0.00	-0.08
Wearing apparel	M	-0.22	-0.18	-0.25	-0.11	-0.09	-0.15	0.03	0.03	0.00	-0.01	-0.01	-0.07
Coal a.lignite; crude petroleum a.natural gas; metal ores	P	-0.24	-0.19	-0.26	-0.13	-0.11	-0.17	-0.01	-0.01	-0.02	-0.06	-0.06	-0.11
Water transport services	S	-0.27	-0.21	-0.29	-0.14	-0.12	-0.17	-0.01	-0.01	-0.03	-0.05	-0.04	-0.10

Table 3.15: Industry-level value added multipliers - government consumption by industry. Sorted according to ex post 1-year multiplier (permanent shock, fourth column). Sectors: services (S), manufacturing (M), construction and utilities (C), mining and agriculture (P).

3.B Model solution and equilibrium

3.B.1 Aggregation and additional variables

- Consumption

$$C_t = \sum_i p_{i,t} c_{i,t} \tag{3.61}$$

- Labor input

  Hours worked by a Keynesian household

$$L_t^K = \sum_i l_{i,t}^K \tag{3.62}$$

  Hours worked by a Ricardian household

$$L_t^R = \sum_i l_{i,t}^R \tag{3.63}$$

  Total hours

$$L_t = \omega^K L_t^K + (1 - \omega^K) L_t^R \tag{3.64}$$

- Private stock of type j capital

$$K_{t-1}^j = \sum_i k_{i,t}^j \tag{3.65}$$

- Total private capital stock (approximate)

$$K_t = \sum_{j=1}^{IK} K_t^j \tag{3.66}$$

- Investment

  Total private investment

$$X_t^R = \sum_{j=1}^{IK} P_t^{X,j} X_t^{R,j} \tag{3.67}$$

  Total government investment

$$X_t^G = \sum_{j=1}^{IK} P_t^{X,j} X_t^{G,j} \tag{3.68}$$

$$X_t = \sum_{j=1}^{IK} P_t^{X,j} X_t^j \tag{3.69}$$

- Industry profits

$$prof_{i,t} = (p_{i,t}^H - RMC_{i,t}) y_{i,t} - RMC_{i,t} \Phi_i \tag{3.70}$$

Aggregate profits

$$T_t = \sum_{i=1}^{I} prof_{i,t} \tag{3.71}$$

- Imports and exports

$$EX_t = \sum_i p_{i,t} ex_{i,t} \tag{3.72}$$

$$IM_t = \sum_i p^F_{i,t} im_{i,t} \tag{3.73}$$

- Aggregate gross output

$$Y_t = \sum_{i=1}^{I} p_{i,t} y_{i,t} \tag{3.74}$$

- Average wages

$$W^K_t = \frac{\sum_i w^K_{i,t} l^K_{i,t}}{L^K_t} \tag{3.75}$$

$$W^R_t = \frac{\sum_i w^R_{i,t} l^R_{i,t}}{L^R_t} \tag{3.76}$$

$$W_t = \frac{\sum_i w_{i,t} l_{i,t}}{\sum_i l_{i,t}} \tag{3.77}$$

- Tobin's Q, denoted Q^T

$$Q^{T,j}_t = 1/\phi_I(\iota^j_t) \tag{3.78}$$

- Inflation in nominal price of investment good of type j

$$\pi^{X,j}_{t+1} = \frac{P^{X,j}_{t+1}}{P^{X,j}_t} \frac{P_{t+1}}{P_t} = \frac{P^{X,j}_{t+1}}{P^{X,j}_t} \pi_{t+1} \tag{3.79}$$

3.B.2 Review of model variables

Exogenous shock processes
A, z_i, $d^{cG}_{i,t}$, $d^{XG}_{j,t}$, $d^{LST^K}_t$, $d^{LST^R}_t$, $d^{\tau^C}_t$, d^{aCG}_t, d^{aXG}_t.
Summary: $6 + I^K + 2 \times I = 11 + 2I$ variables

Government
B^G, C^G, $TaxRev$, $\tau^{l,R}$, $\tau^{l,K}$, X^G, K^G, LST^R, LST^K
Summary: 9 variables

Aggregate variables
K, L, L^K, L^R, X, X^R, C, C^R, C^K, r^k, R, π, EX, IM, $NetExp$, RER, NFA, GDP, VA, Y, W, W^K, W^R, T
Summary: 24 variables

Variables differentiated by capital type

K^j, $K^{G,j}$, X^j, $X^{R,j}$, $X^{G,j}$, $P^{X,j}$, $r^{k,j}$, ι^j
Summary: $8 \times I^K = 40$ variables

Industry variables

y, k, l, l^R, l^K, M, c, c^R, c^K, c^G, ex, im, p, P^M, w, w^R, w^K, RMC, p^*, p^H, p^F
Summary: $21 \times I$ variables

Two dimensional variables

k^j, x^j, $m_{i,j}$
Summary: $2 \times I^K \times I + I \times I = 10 \times I + I \times I$ variables.

Additional and auxiliary variables

λ, Q, $\pi^{X,j}$, $Q^{T,j}$, Ω_i, Ψ_i $prof_i$
Summary: $2 + 2 \times I^K + 3 \times I = 12 + 3 \times I$ variables

Summary

Total number of variables (excl. k^j, x^j, $m_{i,j}$): $41 + 11 \times I^K + 26 \times I = 2020$ variables
Variables k^j, x^j, $m_{i,j}$: $2 \times I^K \times I + I \times I = 6216$ variables

3.B.3 First order conditions

Problem of Ricardian households

Ricardian households maximize their objective function (3.1) with respect to the budget constraint (3.3), capital evolution equation (3.26), non-negativity constraints on K_t^j, $l_{i,t}$ and C_t and two no-Ponzi conditions corresponding to assets B_t, K_t^j. The problem of the household is convex and leads to an interior solution, thus the non-negativity constraints are not binding. We solve the reduced problem of maximizing (3.1) with respect to (3.3) and (3.26) by differentiating the Lagrangian w.r.t. the control variables:

$$C_t^R: \quad \lambda_t(1+\tau_t^C) = U_C(C_t^R, N_t^R) \tag{3.80}$$

$$l_{i,t}^R: \quad -\lambda_t(1-\tau_{i,t}^{l,R})(1-\tau^{s,R})w_{i,t}^R = U_{l_i}(C_t^R, N_t^R) \tag{3.81}$$

$$B_t: \quad \lambda_t = \beta \, \mathrm{E}_t \, \lambda_{t+1}[R_{t+1}^B - \tau^B(R_{t+1}^B - 1)] \tag{3.82}$$

$$K_t^j: \quad \nu_t^j = \beta \, \mathrm{E}_t \left[\nu_{t+1}^j(1-\delta^j + \phi(\iota_{t+1}^j)) + \lambda_{t+1} \tfrac{(r_{t+1}^{k,j} - \tau^k(r_{t+1}^{k,j} - \delta^j)) - (1+\tau^{X,j})P_{t+1}^{X,j}\iota_{t+1}^j}{1-\omega^K} \right] \tag{3.83}$$

$$\iota_t^j: \quad \lambda_t \tfrac{(1+\tau^{X,j})P_t^{X,j}}{1-\omega^K} = \nu_t^j \phi_\iota(\iota_t^j) \tag{3.84}$$

where λ_t and ν_t^j are Lagrange multipliers corresponding to constraints (3.3) and (3.26), respectively. U_C and U_{l_i} denote the derivatives of household objective function w.r.t. the corresponding variables. Equations 3.80 and 3.81 together lead to the intratemporal condition

$$-w_{i,t}^R(1-\tau^{s,R})(1-\tau_{i,t}^{l,R})U_C(C_t^R, N_t^R) = (1+\tau_t^C)U_{l_i}(C_t^R, N_t^R). \tag{3.85}$$

Equations 3.80 and 3.82 together yield the household Euler equation

$$\frac{U_C(C_t^R, N_t^R)}{1+\tau_t^C} = \beta \, \mathrm{E}_t[R_{t+1}^B - \tau^B(R_{t+1}^B - 1)] \frac{U_C(C_{t+1}^R, N_{t+1}^R)}{1+\tau_{t+1}^C}, \tag{3.86}$$

which can be expressed as

$$\frac{1}{C_t^R} = \beta\,\mathrm{E}_t\left[(1-\tau^B)\frac{R_t}{\pi_{t+1}} + \tau^k\right]\frac{1}{C_{t+1}^R}\frac{1+\tau_t^C}{1+\tau_{t+1}^C}. \tag{3.87}$$

Using the standard definition of Tobin's Q (denoted $Q^{T,j}$), equation 3.84 can be rearranged as

$$\nu_t^j = \frac{(1+\tau^{X,j})P_t^{X,j}}{1-\omega^K}\frac{\lambda_t}{\phi_\iota(\iota_t^j)} = \frac{(1+\tau^{X,j})P_t^{X,j}}{1-\omega^K}\lambda_t Q_t^{T,j}, \tag{3.88}$$

and plugged into equation 3.83 to obtain the optimal investment conditions

$$Q_t^{T,j} = \mathrm{E}_t\, Q_{t,t+1}\pi_{t+1}^{X,j}\left[\frac{r_{t+1}^{k,j} - \tau^k(r_{t+1}^{k,j} - \delta^j)}{(1+\tau^{X,j})P_{t+1}^{X,j}} - \iota_{t+1}^j + Q_{t+1}^{T,j}(1-\delta^j + \phi(\iota_{t+1}^j))\right]. \tag{3.89}$$

Problem of Keynesian households

Keynesian households maximize their objective (3.1) with respect to the budget constraint (3.5), and non-negativity constraints on $l_{i,t}$ and C_t. The problem of the household is convex and leads to an interior solution, thus the non-negativity constraints are not binging. Solving the reduced problem of maximizing (3.1) with respect to (3.5) leads to:

$$C_t^K: \quad \lambda_t^K(1+\tau_t^C) = U_C(C_t^K, N_t^K) \tag{3.90}$$

$$l_{it}^K: \quad -\lambda_t^K(1-\tau_{i,t}^{l,K})(1-\tau^{s,K})w_{it}^K = U_{l_i}(C_t^K, N_t^K) \tag{3.91}$$

where λ_t^K is Lagrange multiplier corresponding to constraint (3.5). Equations 3.90 and 3.91 together lead to the intratemporal condition

$$-w_{i,t}^K(1-\tau_{i,t}^{l,K})(1-\tau^{s,K})U_C(C_t^K, N_t^K) = (1+\tau_t^C)U_{l_i}(C_t^K, N_t^K). \tag{3.92}$$

Labor supply wedge: wage rigidity

We implement the real wage rigidity in a reduced form by introducing a wedge in the optimal labor supply decisions 3.85, 3.92. The households supply labor according to the following equation:

$$-w_{i,t}^S = \left(\frac{(1+\tau_t^C)U_{l_i}(C_t^S, N_t^S)}{(1-\tau_{i,t}^{l,S})(1-\tau^{s,S})U_C(C_t^S, N_t^S)}\right)^{(1-\omega)}\left(w_{i,ss}^S\right)^\omega, \tag{3.93}$$

for $S \in \{K, R\}$. Notice that equation 3.93 has the same steady state as equation 3.85 resp. 3.92 but implies a dampened reaction of wages compared to labor supply for any $0 < \omega \leq 1$. The case $\omega = 0$ corresponds to conditions 3.85 and 3.92.

Firm problem

Given the firm prices, the demand for products of each firm is determined. Firm k in industry i faces the problem of optimal choice of production inputs, such that the demand is satisfied.

$$\min_{k^j_{ki,t}, l^S_{ki,t}, m_{k,1..I,i,t}} (1-\omega^K) w^R_{i,t} l^R_{ki,t} + \omega^K w^K_{i,t} l^K_{ki,t} + \sum_{j=1}^{I^K} r^{k,j}_t k^j_{ki,t} + (1+\tau^{M,i}) \sum_{j=1}^{I}, p_{j,t} m_{k,ji,t} \tag{3.94}$$

such that

$$y_{ki,t}(p_{ki,t}) + \Phi_i = F^i(A_t, z_{i,t}, k_{ki,t}, l_{ki,t}, M_{ki,t}, K^G_{t-1}), \tag{3.95}$$

where F^i is the production function in industry i and input aggregates $l_{ki,t}$, $k_{ki,t}$, $M_{ki,t}$ are defined according to equations 3.15 - 3.17, respectively. We denote $w_{i,t}$, $r^k_{i,t}$, $P^M_{i,t}$ the corresponding price indexes, respectively. Due to the constant returns to scale technology, the price indexes of all production factors are the same for all firms in industry i, as they optimally choose the same composition of inputs.

Differentiating the Lagrangian w.r.t. $l_{ki,t}$, $k_{ki,t}$, $M_{ki,t}$ we obtain the standard conditions

$$\frac{w_{i,t}}{\lambda_{ki,t}} = \frac{\partial F^i}{\partial l_{ki,t}}, \tag{3.96}$$

$$\frac{r^k_{i,t}}{\lambda_{ki,t}} = \frac{\partial F^i}{\partial k_{ki,t}}, \tag{3.97}$$

$$(1+\tau^{M,i})\frac{P^M_{i,t}}{\lambda_{ki,t}} = \frac{\partial F^i}{\partial M_{ki,t}}, \tag{3.98}$$

where $\lambda_{ki,t}$ is the Lagrange multiplier associated with condition 3.95.

The wage index of labor used in industry i, $w_{i,t}$, follows from the constant returns to scale function of labor input l_i,

$$w_{i,t} = \left((1-\omega^K)(w^R_t)^{1-\sigma_l} + a^K_i \omega^K (w^K_t)^{1-\sigma_l}\right)^{\frac{1}{1-\sigma_l}}. \tag{3.99}$$

Firm demand for the two types of labor follows

$$l^R_{ki,t} = \left(\frac{w^R_{i,t}}{w_{i,t}}\right)^{-\sigma_l} l_{ki,t}, \tag{3.100}$$

$$l^K_{ki,t} = a^K_i \left(\frac{w^K_{i,t}}{w_{i,t}}\right)^{-\sigma_l} l_{ki,t}. \tag{3.101}$$

The capital good k_i is the same across industries, therefore its unit price (index) $r^k_{i,t} = r^k_t$ must be the same across industries and follows from the production function of capital aggregate k_i:

$$r^k_t = \left(\sum_{j=1}^{I^K} \chi^j \left(r^{k,j}_t\right)^{1-\sigma_k}\right)^{\frac{1}{1-\sigma_k}}. \tag{3.102}$$

Firm demand for the various types of capital follows

$$k^j_{ki,t} = \chi^j \left(\frac{r^{k,j}_t}{r^k_t}\right)^{-\sigma_k} k_{ki,t}. \tag{3.103}$$

The price index of intermediate goods used in industry i, $P^M_{i,t}$, follows from the production function of intermediate good M_i:

$$P^M_{i,t} = \left(\sum_{j=1}^{I} \alpha_{ji} {p_{j,t}}^{1-\sigma_M}\right)^{\frac{1}{1-\sigma_M}}. \tag{3.104}$$

Combining conditions 3.96 and 3.97 lead to

$$\frac{w_{it}}{r^k_t} = \frac{\partial F^i/\partial l_{ki,t}}{\partial F^i/\partial k_{ki,t}}, \tag{3.105}$$

and combining conditions 3.97 and 3.98 gives

$$\frac{w_{it}}{(1+\tau^{M,i})P^M_t} = \frac{\partial F^i/\partial l_{ki,t}}{\partial F^i/\partial M_{ki,t}}. \tag{3.106}$$

Following a standard procedure, it is straightforward to derive the optimality condition

$$RMC_{i,t} = \frac{r^k_t}{\partial F^i/\partial k_{ki,t}}, \tag{3.107}$$

and analogous conditions for $l_{ki,t}, M_{ki,t}$, where the real marginal costs are

$$RMC_{i,t} = \frac{1}{J_t A_t z_{i,t}} \left(\mu_{i,K} {r^k_t}^{1-\sigma_y} + \mu_{i,L} {w_{i,t}}^{1-\sigma_y} + \mu_{i,M}\left((1+\tau^{M,i})P^M_{i,t}\right)^{1-\sigma_y}\right)^{\frac{1}{1-\sigma_y}}, \tag{3.108}$$

are independent on the firm's decisions. Equation 3.107 thus implies that all firms operating in industry i choose inputs such that the partial derivatives $\partial F^i/\partial k_{ki,t}$ are the same across firms. Equations 3.105 to 3.107 thus hold at the industry level as well. Apart from the fixed costs, the production technology is constant returns to scale, therefore real costs are linear in output,

$$Costs(y_{ki,t} + \Phi_i) = RMC_{i,t} \times (y_{ki,t} + \Phi_i). \tag{3.109}$$

Plugging the production function 3.14 into 3.107 and reorganizing, we get

$$k_{ki,t} = (J_t A_t z_{it})^{\sigma_y - 1} \mu_{i,K} \left(\frac{r^k_t}{RMC_{i,t}}\right)^{-\sigma_y} (y_{ki,t} + \Phi_i), \tag{3.110}$$

and corresponding equations for labor and intermediate inputs.

Industry quantities

Industry demand for labor follows from the market clearing condition

$$l_{i,t} = \int_0^1 l_{ki,t}\, dk \tag{3.111}$$

$$= \Theta_{i,t} \int_0^1 y_{ki,t} + \Phi_i\, dk \tag{3.112}$$

$$= \Theta_{i,t}\Phi_i + \Theta_{i,t} y_{i,t} \int_0^1 \left(\frac{p_{ki,t}}{p^H_{i,t}}\right)^{-\sigma_I} dk, \tag{3.113}$$

where constant $\Theta_{i,t}$ depends on industry-level prices and parameters only,

$$\Theta_{i,t} = (J_t A_t z_{it})^{\sigma_y - 1} \mu_{i,L} \left(\frac{w_{i,t}}{RMC_{i,t}}\right)^{-\sigma_y}. \tag{3.114}$$

We define the dispersion term

$$Disp_{i,t} = \int_0^1 \left(\frac{p_{ki,t}}{p^H_{i,t}}\right)^{-\sigma_I} dk. \tag{3.115}$$

A standard result from the New Keynesian literature shows that the dispersion term has only second-order effects around the zero-inflation steady state. It follows that

$$l_{i,t} \approxeq (J_t A_t z_{it})^{\sigma_y - 1} \mu_{i,L} \left(\frac{w_{i,t}}{RMC_{i,t}}\right)^{-\sigma_y} (y_{i,t} + \Phi_i), \tag{3.116}$$

up to the first order approximation.

We now derive the total demand for a particular good i and show it is independent of firm-specific variables up to the first order approximation. We start with determining the demand for i as intermediate input. In line with 3.116, demand for intermediate good aggregate $M_{j,t}$ in industry j is

$$M_{j,t} \approxeq (J_t A_t z_{j,t})^{\sigma_y - 1} \mu_{j,M} \left(\frac{(1 + \tau^{M,j}) P^M_{j,t}}{RMC_{j,t}}\right)^{-\sigma_y} (y_{j,t} + \Phi_j). \tag{3.117}$$

An optimizing firm k in sector j chooses intermediate input from sector i according to

$$m_{k,ij,t} = \alpha_{ij} \left(\frac{p_{i,t}}{P^M_{j,t}}\right)^{-\sigma_M} M_{kj,t} \tag{3.118}$$

Total intermediate input i as an input into industry j production can be expressed as

$$m_{ij,t} = \int_0^1 m_{k,ij,t}\, dk \tag{3.119}$$

$$= \alpha_{ij} \left(\frac{p_{i,t}}{P^M_{j,t}}\right)^{-\sigma_M} \int_0^1 M_{kj,t}\, dk \tag{3.120}$$

$$\approxeq \Gamma_{ij,t}(y_{j,t} + \Phi_j), \tag{3.121}$$

where the parameter $\Gamma_{ij,t}$ is independent of the firm's actions,

$$\Gamma_{ij,t} = \alpha_{ij}\mu_{j,M}(J_t A_t z_{j,t})^{\sigma_y - 1}\left(\frac{p_{i,t}}{P^M_{j,t}}\right)^{-\sigma_M}\left(\frac{(1+\tau^{M,j})P^M_{j,t}}{RMC_{j,t}}\right)^{-\sigma_y}. \tag{3.122}$$

Thus, the total demand for industry i's good can be expressed as

$$\begin{aligned} y_{i,t} &= c_{i,t} + c^G_{i,t} + \sum_{j=1}^{I^K} x^j_{i,t} + \sum_{j=1}^{I} m_{ij,t} + ex_{i,t} - im_{i,t} && (3.123)\\ &\approx v_i p_{i,t}{}^{-\sigma_C}((1-\omega^K)C^R_t + \omega^K C^K_t) + c^G_{i,t} + \sum_{j=1}^{I^K} \nu_i^{X,j}\left(\frac{p_{i,t}}{P^{X,j}_t}\right)^{-\sigma_X} X^j_t + && (3.124)\\ &+ \sum_{j=1}^{I} \Gamma_{ij,t}(y_{j,t} + \Phi_j) + ex_{i,t} - im_{i,t}. && (3.125) \end{aligned}$$

Price setting

The period $t+s$ demand for the product of a firm that has last updated its price in period t can be expressed using 3.12 as

$$y_{ki,t+s|t} = \left(\frac{p^{NOM}_{ki,t}}{p^{H,NOM}_{i,t+s}}\right)^{-\sigma_I} y_{i,t+s}, \tag{3.126}$$

where superscript NOM denotes the nominal prices. Equation 3.125 shows that $y_{i,t+s}$ does not depend on the decisions of firm k.

The price-setting problem of each firm is to maximize 3.20:

$$\max_{p_{ki,t}, y_{ki,t}, .., y_{ki,\infty}} \mathrm{E}_t \sum_{s=0}^{\infty} \theta_i{}^s Q_{t,t+s}\left[y_{ki,t+s|t}(p^{NOM}_{ki,t} - NMC_{i,t+s}) - \Phi_i NMC_{i,t+s}\right]. \tag{3.127}$$

with respect to 3.126. Nominal marginal costs $NMC_{i,t}$ are defined as

$$NMC_{i,t} = P_t \cdot RMC_{i,t}. \tag{3.128}$$

Differentiating the Lagrangian we obtain

$$\begin{aligned} p^N_{ki,t} &: \mathrm{E}_t \sum_{s=0}^{\infty} \theta_i{}^s Q_{t,t+s} y_{ki,t+s|t} - \sum_{s=0}^{\infty} \varrho_{t+s}\sigma_I \frac{(p^{NOM}_{ki,t})^{-\sigma_I - 1}}{(p^{H,NOM}_{i,t+s})^{-\sigma_I}} y_{i,t+s} = 0, && (3.129)\\ y_{ki,t+s|t} &: \theta_i{}^s Q_{t,t+s}[p^{NOM}_{ki,t} - NMC_{i,t+s}] = -\varrho_{t+s}, && (3.130) \end{aligned}$$

ϱ_t denoting the Lagrange multiplier corresponding to the constraint 3.126 at time t. Substituting

3.130 into 3.129 we get

$$\mathrm{E}_t \sum_{s=0}^{\infty} \theta_i{}^s Q_{t,t+s} \left[y_{ki,t+s|t} - [p^{NOM}_{ki,t} - NMC_{i,t+s}]\sigma_I \frac{(p^{NOM}_{ki,t})^{-\sigma_I - 1}}{(p^{H,NOM}_{i,t+s})^{-\sigma_I}} y_{i,t+s} \right] = 0 \tag{3.131}$$

$$\mathrm{E}_t \sum_{s=0}^{\infty} \theta_i{}^s Q_{t,t+s} y_{ki,t+s|t} \left[p^{NOM}_{ki,t} - \frac{\sigma_I}{\sigma_I - 1} NMC_{i,t+s} \right] = 0 \tag{3.132}$$

In a symmetric equilibrium, all firms within an industry i that set their prices in period t choose the same optimal price $p^{NOM}_{ki,t} = p^{NOM*}_{i,t}$.

The numerical solution of the the model requires us to express the FOC 3.132 in terms of recursively defined sums. We can derive that the equation is equivalent to (in real prices)

$$\Omega_{i,t} p^*_{i,t} = \mu \Psi_{i,t} p^H_{i,t}, \tag{3.133}$$

where the recursive expressions for Φ and Ψ give

$$\Omega_{i,t} = y_{i,t} + \theta_i \, \mathrm{E}_t \left(\frac{p_{i,t+1}}{p_{i,t}} \pi_{t+1} \right)^{\sigma_I} Q_{t,t+1} \Omega_{i,t+1}, \tag{3.134}$$

$$\Psi_{i,t} = y_{i,t} \frac{RMC_{i,t}}{p_{i,t}} + \theta_i \, \mathrm{E}_t \left(\frac{p_{i,t+1}}{p_{i,t}} \pi_{t+1} \right)^{\sigma_I + 1}. \tag{3.135}$$

3.B.4 Equilibrium

The equilibrium allocation is determined by the following set of $41 + 11 \times I^K + 26 \times I$ equations, which determine the variables listed in section 3.B.2

Industry-level equations

- I exogenous shock processes for industry productivity 3.54
- I exogenous shock processes for government consumption 3.52
- I FOCs from Ricardian household problem 3.85
- I FOCs from Keynesian household problem 3.92
- I production functions 3.14
- $3I$ FOCs from firm cost optimisation 3.105 - 3.107
- $2I$ conditions firm demand for labor input by household type 3.100, 3.101
- $3I$ recursive formulation of FOCs of firm price setting problem 3.133 - 3.135
- I industry home price evolution equations 3.19
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- I industry price equations 3.45
- $2I$ optimal demand for industry good in final consumption by type 3.8
- I total demand for industry good in final consumption 3.48
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3.B.5 Numerical solution

We solve the model by linearising the equations around the deterministic steady state. In the first step, we find the deterministic steady state. In the second step, the linear solution is computed in HetSol Toolkit developed by Michael Reiter.

3.C Data and Calibration

3.C.1 Additional information on data sources

To characterise the two types of households we use the data from the 2016 EU Statistics on income and living conditions in Austria published by Statistics Austria, (StatAT 2017). The EU-SILC database gathers the information on income, government transfers, and other income-related statistics from 6,000 individual households representative of all 3.9 million households in Austria. We used the so-called h-file of the EU-SILC database in order to determine household characteristics. In order to determine the type of household, we used the information about household income (income of all household members). Given the type of household, all its members were also assigned the same type. The characteristics of workers of each type in different industries were then identified using the personal p-file of EU-SILC database. The industry/household type characteristics, e.g. gross wages, tax base, average and marginal tax rates, were determined based on the personal characteristics of the corresponding workers.

3.C.2 Description of the data inputs

This section lists the data inputs needed for the calibration of the deterministic steady state of the model and describes the construction of the targets. For the sake of readability, we omit the industry indices from the names of industry-level variables. The IOT information is reported in nominal values (current Euros). We remove the effect of growth and inflation by normalizing the values by the size of the economy (in terms of value added) in each year before computing the averages. String *ndat* in the names of input variables indicates nominal values.

Gross output: yndat

Gross output in the IOT includes value added, intermediate inputs and product taxes and subsidies on intermediate inputs, which is consistent with the model. Thus, the input variable *yndat* equals IOT 28, row *Output at basic prices*. A cosmetic adjustment is implemented in order to satisfy the IOT identities, see the following section.

Intermediate inputs: mndat

The intermediate input accounts are consistent with the model. $I \times I$ table *mndat* directly equals the intermediate inputs of the IOT 28.

In industry *97 - Services of households as employers of domestic personnel* we increased the intermediate input from the industry into itself by a negligible amount to prevent technical difficulties connected to zero values of factor inputs. In order to preserve the input-output identities, we added the same amount to gross output in this industry.

Product tax on intermediate inputs: mtaxndat

Product taxes payed on intermediate inputs purchases are reported separately for each (purchasing) industry. We use this information to calibrate the industry-specific effective rates for this tax. We compute variable *mtaxndat* as the sum of IOT rows *Taxes on products* plus *Subsidies on products*, where subsidies are small relative to the taxes.

Value added: vandat

Value added in the IOT includes all gross payments to labor, capital, operating surplus (profits), as well as taxes and subsidies on production. This accounts are consistent with the concept of value added in the model. The input variable *vandat* equals IOT row *Value added at basic prices.*

However, some problems in consistency arise for the components of value added. *Operating surplus* in the IOT include both profits and labor renumeration of the self-employed persons. *Other taxes on production* include labor and labor income-based taxes, capital-based taxes and other types of production taxes. See the discussion below for more detail.

Capital remuneration and profits: kndat

Identifying the capital and labor shares consistently with the model specification belongs to the most problematic part of the IOT processing. The reasons are that

1. the two components (in the economic sense) are mixed in the IOT accounting,
2. multiple values are not consistent with the assumption that the IOT information constitutes a steady state,
3. there are discrepancies between the role of public capital in the model and the IOT.

However, we process the IOT information such that the labor and capital share are reasonably approximated: the resulting capital share (including profits) and labor share (gross with taxes) add up to the value added and are both non-negative. Further, we target the steady state share of aggregate profits on value added. We assume that profits in each industry are proportional to its capital share and decompose the share into the remuneration of capital and profits.

With respect to the third point, the issue arises because public capital in the model is not a production factor creating public output, but merely acts as a special type of public consumption with an additional persistent positive effect on the aggregate productivity in the rest of the economy.

Investments of publicly owned companies which create value added and yield (accounting) profits or losses are not considered in the model. The model restricts value added to equal private labor share plus private capital share.

In this paper, we assume that all profits, returns on capital and capital depreciation in the IOT belong to the investment of the private sector. We define public investment share in line with the national accounts (VGR), which is relatively restrictive (many companies closely related to the state sector are included in private sector according to the VGR). Although using this definition reduces the discrepancy, it does not resolve it fully. A consequence of the assumption is that the steady state returns and profits from private capital and the depreciation of capital are potentially underestimated. However, the depreciation rates depend on two other free parameters (steady state profits share $shProf$ and nominal interest rate R), which we can use to offset the bias.

Given these assumptions, the capital share consisting of gross capital remuneration and profits is equal to IOT profits and returns on capital (*Operating surplus, net*) plus depreciation (*Consumption of fixed capital*) plus taxes on capital and capital income (parts of *Other taxes on production* and *Other subsidies on production*). The following adjustments affect the construction of the capital share:

- **Negative capital remuneration**: for some industries and some years, net operating losses are so large that gross capital remuneration becomes negative. This is technically impossible in the model, as capital and profits can not be negative in steady state. In the data, this occurs either due to contractionary economic shocks (industry far from the steady state), or possibly due to inadequate accounting for state-owned enterprises and capital (reporting losses instead of state subsidies).

  To minimize the effects of the extreme values, we use averages across 2012-2014. Moreover, we make several ad-hoc adjustments to the data:

  1. Industry *19 - Coke and refined petroleum products* reports extremely huge capital share for 2013 and 2014. For a conservative estimate, we replaced these with 2012 value.
  2. Industry *42 - Constructions a. construction works for civil engineering* reports negative capital share for all years. We choose to replace the capital share in this industry by a closely related industry (*41 - Buildings and building construction works*).
  3. Industry *51 - Air transport services* reports inadequately low capital shares. We choose to replace the share by the economy-wide average (ca. 0.37), which is still a very low estimate for this industry.
  4. We replace the zero capital share of *97 - Services of households as employers of dom. personnel* with the (closest to zero) share in *87-88 - Residential care services, social work services.*

- **Negative operating surplus**: In about 10 other industries, net operating surplus in IOT is negative on average over 2012-2014. Most of the industries appear to be dominated by state-run enterprises. Although this does not impose technical difficulties, it affects the implied gross returns on capital and the depreciation rates.

- **Remuneration of self-employed:** Earnings of self-employed including their social insurance contributions are accounted for as operating surplus. However, from the economic perspective they are labor income. In a handful of industries, this creates a substantial discrepancy.

  We use the information from IOT Table 27 to compute the share of hours worked by self-employed in each industry. For the lack of other information, we assume that gross earnings per hour are the same for self-employed and employed.[5] Additionally, we restrict the remuneration of the self-employed in each industry to be at most as high as operating surplus and at least zero.

- **Other taxes and subsidies on production**: *Other taxes/subsidies on production* are assigned to the capital and labor share proportionally to their relative size in each industry. We use the information on tax income by base from the Austrian national tax list, distinguishing between taxes based on employment and labor income vs. other bases for taxes in this category. Labor-income or employment-based taxes account for 75% of the revenues of other taxes on production. We use the information to correct the factor shares. Subsidies are negligible in most of the industries. We deal with the subsidies by reducing the tax in each industry by the amount of subsidies.

Lastly, we apply the capital and labor shares to split the value added of the IOT. In this way we get nominal labor and capital remuneration estimates consistent with value added.

Labor remuneration of Keynesian and Ricardian households:
lKndat, lRndat, wKdat, wRdat

Total nominal labor share (*lndat*) follows as the sum of IOT items *Wages and salaries*, *Employers' social contributions*, estimated remuneration of self-employed, and the implied share of *Other taxes on production + Other subsidies on production*, see the previous paragraph for detail.

The IOT tables do not distinguish between various types of households, thus the information about the labor input of Keynesian and Ricardian household is missing. We supplement the IOT data with the information from the EU-SILC database to calculate relevant shares at the level of industries. First, the 90 industries differentiated in the EU-SILC database needed to be matched to the classification used in the IOT. Second, for each industry, we identified the number of workers belonging to a Ricardian or a Keynesian household. Based on this information, we calculated the total gross compensation per industry and household type, and the respective shares. With respect to those industries that did not have enough observations to consider the average gross compensation by household type representative, we aggregated similar industries into groups. We used the more robust information on gross compensation of the groups to obtain the shares for the two household types, and assumed the shares are representative for each of the individual industries belonging to a group.

[5] the assumption appears in other growth accounting studies, see e.g. (Timmer et al. 2007b).

Finally, the labor remuneration of Keynesian households in each industry is

$$lKndat = \frac{lKn_{silc}}{ln_{silc}} lndat, \tag{3.136}$$

where lKn_{silc} is the gross labor income of Keynesians reported in SILC, ln_{silc} is the gross labor income of all workers reported in SILC and lndat in the IOT information on labor remuneration.

We use the information about total hours from IOT 27 and SILC data in order to identify total hours (real labor input) worked by Keynesian and Ricardian households,

$$h^K = \frac{h^K_{silc}}{h_{silc}} h^{tot}. \tag{3.137}$$

The number of total hours worked by industry and household type were determined in analogy to the calculation of gross compensation per industry and type. Hourly wages of Keynesians and Ricardians (w^K, w^R) then follow from labor remuneration and hours.

Consumption: pcndat, gcndat

There are three consumption entities in the IOT: households, government, and non-profit organisations. We define private consumption *pcndat* as household consumption and non-profit organisations together. Government consumption *gcndat* is consistent with the government consumption from the IOT.

Investment: xRndat, xGndat

The IOT tables feature six different categories of gross fixed capital formation. We aggregate the IOT capital types *Cultivated assets* and *Intangible fixed assets* together into category *Intangible and other investment* The investment accounts are otherwise consistent between the model and the IOT. The investment rates together with the depreciation rates determine the steady state composition of capital.

However, for each type of capital we need to differentiate between the investment of public and private sector. There is no distinction between public and private investment in the IOT. To determine the share of public investment in total investment we used the information from the national accounts, tables 57, as reported by the Austrian statistical office (StatAT 2018). We computed the average share of public investment over the years 2013 - 2017 and applied the share to all five types of investment. In this period, the share of public investment was stable and close to 13% in all years.

Exports and imports: expndat, impndat

The steady state exports and imports *expndat*, *impndat* are essentially consistent with the input-output tables, categories *Total Exports* and *Imports*.

In order to satisfy the identities, we add two additional final use categories without a model counterpart to exports and imports. Categories *Changes in valuables* and *Changes in inventories* are typically very small compared to exports and imports.

Product tax on final uses: ctaxndat, cgtaxndat, xtaxndat

Product taxes payed on final uses in the IOT are reported separately for each use. We compute the effective taxes as the sum of IOT rows *Taxes on products* plus *Subsidies on products*, where subsidies are typically small relative to taxes. Private consumption tax *ctaxndat* is computed as the sum of taxes payed by private households and non-profit institutions.

Total tax revenues: TaxRev_ss

We calibrate the total tax revenues in steady state to match the total tax revenues from the National tax list. We compute the tax revenues relative to value added for 2012-2014 and use the average across the three years. The model features a lump sum residual tax which ensures that total tax revenues are consistent with the calibrated tax rates.

Tax rates τ

The model features nine types of flat tax rates: $\tau^{l,S}$, τ^{s}, τ^{k}, τ^{C}, τ^{CG}, $\tau^{X,j}$, $\tau^{M,i}$, τ^{B}, τ^{BG}. We calibrate the rates to match corresponding average tax rates in the data.

τ^C **Product taxes** $\tau^{M_i,C,CG,X}$ are computed directly from the IOT 28, see above.

τ^k **Profits and capital income tax**
We use information on total capital income and corporate taxes as a share of total gross value added between 2012 and 2014 from the National tax list to pin down the rate. We also include production taxes which are payed based on a non-labor related base.

τ^B **Asset income (interests on private bonds) tax**
The steady state bond holding in the model does not reflect the realistic volumes, thus the total tax revenue can not be matched. However, the discrepancy is offset by the residual tax $ResT$. To calibrate the marginal rate on interests from private bonds τ^B, we use the information on statutory tax rates on interests, which is approximately 25%. The statutory tax rate applies on nominal interest payments, while in our model, only the real interests above the trend growth are being taxed. Therefore, we need to adjust the tax rate for this discrepancy.

τ^{BG} **Asset income (interests on government bond) tax**
The steady state bond holding in the model does not reflect the realistic volumes, thus the total tax revenue can not be matched. However, the discrepancy is offset by the residual tax $ResT$. We set the marginal rate on interests from government bonds τ^{BG} close to zero, as the majority of the Austrian government bonds is held by foreign agents and the income from these bonds is primarily taxed abroad.

τ^s **Social insurance contributions**
We assume the rate τ^s is independent of the household type. We use the information on total social insurance contributions as a share of total gross value added between 2012 and

2014 from the National tax list to pin down the rate. The share is on average ca. 17% of gross value added, which represents ca. 27% rate on total labor costs in the steady state.

A major adjustment of the rate is conducted in order to account for the effect of shocks on government transfers. As unemployment is not modelled separately in our model, the effective social insurance contributions tax also takes into account the average gain in unemployment benefit payments. We use the information from the national accounts to calibrate the average unemployment benefits payments, see table D.62 StatAT (2018). The unemployment remuneration is also assumed to be independent of the household type. The adjusted rate τ^s is roughly 29%.

τ^l **Labor income taxes**

We use the information on total labor and mixed income taxes as a share of total gross value added between 2012 and 2014 from the National Tax List to pin down the total tax revenues. We include all production taxes which are paid based on labor income or labor input.

We used the additional information about the income of workers from the EU-SILC data in order to split the total revenues by industry and household type. For each observed worker, we computed the tax base by deducting the social insurance and other deductibles from the gross wages. Subsequently, we assigned the marginal tax rates according to the corresponding tax bracket, see BMF (2014). We calculated the average tax rate for each worker as a corresponding weighted average across the tax rate brackets. We computed the (SILC) average and marginal tax rates by industry and household type by aggregating over the individual representative observations.

In the last step, the relative size of tax revenues collected from Ricardian and Keynesian households implied by the EU SILC data was applied in order to split the total labor income revenues from the National Tax List. The average tax rates for Keynesian and Ricardian households $\tau^{l,K}$ and $\tau^{l,R}$ are calculated to match the tax revenues in the steady state.

Shares of government transfers received by the Ricardian and Keynesian households: LSTR_sh, LSTK_sh

Relative size of government transfers received by Keynesian and Ricardian households is calibrated using the information on transfer payments from the EU SILC data. The resulting shares are providing a rough approximation of the lump sum transfers in the model. However, the model impulse-response functions are extremely robust with respect to the calibration of the shares.

Depreciation rate by capital type (relative sizes): d^j

The five types of capital in our model differ in their depreciation rates. We use the information on depreciation rates published by Statistics Austria to pin down the relative sizes of depreciation rates δ^j of the five capital types (StatAT 2018, p.212).

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Abstract

This thesis consists of three essays that study dynamic stochastic general equilibrium models at the level of industries. The first essay examines the importance of industry-level evidence for testing various explanations of the vanishing cyclicality of productivity in the U.S. in the mid-1980s. The second essay studies the implications of a medium-sized New Keynesian industry-level model for the identification of sources of business cycles. The third essay focuses on the effects of fiscal policy shocks in a small open economy model. The unifying feature of the three essays is the presence of a highly disaggregated industry structure with more than seventy industries connected via the input-output network.

In the first essay I construct a simple industry-level RBC model that nests two leading explanations of the vanishing cyclicality of productivity that have been proposed in the literature. I show that the explanations have qualitatively different predictions for the cyclical properties of industry-level variables. Only the mechanism based on a structural change in the composition of aggregate shocks is able to generate the vanishing cyclicality of productivity without counterfactual changes in industry-level moments.

The second essay studies the relative importance of demand and technology shocks in generating business cycle fluctuations in the U.S. We find that the aggregate technology shock has zero variance. Exogenous shocks to technology are necessary for our model to fit the data, but these shocks are exclusively industry-specific. The bulk of the aggregate fluctuations are explained through the shocks to aggregate demand. This shock structure is supported by a host of information from the disaggregate data.

Finally, the third essay studies fiscal multipliers in an industry-level New Keynesian small open economy model calibrated with Austrian data. We show that the model predicts a very high heterogeneity across multipliers for government spending in different industries. We show that the major sources of this heterogeneity are (1) differences in import shares across industries, (2) production factor shares, and (3) asymmetry of the input-output network. Government consumption shocks in some industries may generate higher short-run multipliers compared to government investment, especially in the case of temporary policy interventions.

Zusammenfassung

In dieser Dissertation untersuche ich drei multisektorale dynamische stochastische allgemeine Gleichgewichtsmodelle. Der erste Artikel verwendet Branchendaten zur Prüfung verschiedener Erklärungen für die verschwindende Zyklizität der Produktivität in den USA Mitte der 1980er Jahre. Der zweite Artikel untersucht die Folgerungen aus einem mittelgroßen Neu-Keynesianischen Modell für die Identifikation der Quellen von Konjunkturzyklen. Der dritte Artikel analysiert die Auswirkungen fiskalpolitischer Schocks in einem Modell einer kleinen offenen Wirtschaft. Das verbindende Merkmal der drei Artikel ist die stark disaggregierte Industriestruktur mit mehr als siebzig Branchen, die über Input-Output-Beziehungen miteinander verbunden sind.

Im ersten Artikel entwickle ich ein einfaches RBC-Modell auf Branchenebene, das zwei in der Literatur vorgeschlagene Erklärungen für die verschwindende Zyklizität der Produktivität gegeneinander abtestet. Ich zeige, dass die beiden Erklärungsansätze qualitativ unterschiedliche Vorhersagen für die zyklischen Eigenschaften der Variablen auf Branchenebene haben. Nur die strukturelle Veränderung in der Zusammensetzung der aggregierten Schocks kann die verschwindende Zyklizität der Produktivität ohne kontrafaktische Veränderungen der Momente auf Branchenebene erzeugen.

Der zweite Artikel untersucht die relative Bedeutung von Nachfrage- und Produktivitätsschocks zur Generierung der Konjunkturschwankungen in den USA. Wir stellen hinsichtlich der Produktivitätsschocks fest, dass branchen-spezifische Schocks ausreichend sind, damit unser Modell die Daten replizieren kann. Der aggregierte Produktivitätsschock wird folglich nicht benötigt. Der Großteil der aggregierten Fluktuationen wird durch die aggregierten Nachfrageschocks erklärt. Diese Schockstruktur wird durch eine Vielzahl der Informationen aus den disaggregierten Daten unterstützt.

Schließlich untersuchen wir im dritten Artikel Fiskalmultiplikatoren in einem Neu-Keynesianischen Modell einer kleinen offenen Volkswirtschaft auf Branchenebene, das auf österreichische Daten kalibriert wurde. Wir zeigen, dass das Modell eine sehr hohe Heterogenität zwischen den Staatsausgabenmultiplikatoren der verschiedenen Branchen impliziert. Die Ursachen für diese Heterogenität sind (1) Unterschiede in der Importintensität der verschiedenen Branchen, (2) Unterschiede in Lohnquote und Zwischenproduktintensität der Branchen und (3) die Asymmetrie des Input-Output-Netzwerks. In einigen Industriezweigen übertrifft der kurzfristige Multiplikator des Staatskonsums den der staatlichen Investitionen, insbesondere im Falle temporärer Interventionen.