The Cycle is the Trend: Firm-level Evidence on Hysteresis Effects in TFP

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Abstract

This paper presents firm-level empirical evidence on technology-enhancing investment in a crisis using a large representative survey of German firms and links it to hysteresis effects in TFP. We show that about 25% of firms decreased their investment in R&D and 20% in technology adoption respectively. These reductions are large and economically meaningful and causally linked to the COVID-19 crisis episode. This result contradicts standard theory which assumes that recessions do not influence technology growth and thus the long-run trend. Using firm-specific information, we derive the determinants of hysteresis at the firm level to inform monetary and fiscal policy on well-targeted tools to reduce long-run scars of recessions. We identify demand shocks as a key driver of firms' reduction in innovation investment which supports the view that short-run aggregate demand affects long-run aggregate supply. Our empirical results are rationalized by a New Keynesian DSGE model with endogenous technology-enhancing investment and long-run trend dynamics and speak against the traditional dichotomy between cycle and trend.

JEL classification: D22, E22, E24, E32, 030, 040

Keywords: Hysteresis, Endogenous Growth, Innovation, Demand Shocks, Firm-level Data

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1 Introduction

Standard macroeconomic models study cycle and trend strictly separately. Conventional New Keynesian models, for instance, abstract from modeling TFP dynamics endogenously and, instead, study cyclical fluctuations around an exogenous long-run trend, which is assumed to be determined by long-run, structural factors only. Any short-run fluctuations in TFP, in turn, are attributed to exogenous technology shocks. These assumptions, however, hold a set of non-trivial implications. Firstly, there is a strict dichotomy of cycle and trend as cyclical fluctuations do not influence technology-enhancing investment and thus the long-run trend path. Moreover, hysteresis effects, i.e. long-run effects of in itself transitory shocks, are ruled out by assumption and aggregate output reverts even after pronounced recessions back to pre-crisis trend. Further, TFP and its key driver technology growth are supply-side determined and in particular demand shocks exert no influence on long-run aggregate supply.
The recent literature (see Cerra et al. (2020) for a review), however, emphasizes the role of hysteresis effects in TFP both theoretically and empirically. In particular, contractionary, transitory shocks can have long-run effects to the extent that they reduce technology-enhancing investment and thus TFP and the long-term aggregate output path. While there is increasing evidence on the importance of these channels using aggregated data, micro evidence on hysteresis effects in TFP is very scarce at this stage. This paper bridges this gap and provides firm-level evidence on the procyclicality of technology-enhancing investment and hysteresis effects in TFP. We study these channels using a large, representative survey of German firms which contains granular information on the investment plans, actual decisions and magnitudes of different margins of investment in innovation (R&D, technology adoption, digitalization) alongside detailed firm characteristics and, crucially, information on the main driving forces and key firm-level constraints behind adjustment of investment in innovation in the most recent crisis. This paper thus provides insights into the determinants of hysteresis at the firm-level and establishes a causal link between cyclical changes in economic conditions and the adjustment of investment in innovation at the firm-level as well as the role of the central driving shocks in this context. By means of these granular information on the firm-level we further aim at informing monetary and fiscal policy as to the design of well-targeted policy tools to alleviate hysteresis effects in TFP and thus the long-run scars of recessions. As shown in Figure 1, aggregate innovation expenditure in Germany experienced a pronounced drop in the context of the COVID-19 crisis which, moreover, stands in sharp contrast to planned innovation expenditures pre-crisis.

Our main results can be summarized as follows. About 30% of firms with plans to conduct R&D changed their planned R&D investment in 2020 as a response to the COVID-19 crisis, out of which the majority reduced their investment. This result not only holds for frontier innovation through research and development, but also for non-frontier innovation activities, i.e. technology adoption. About a quarter of the firms which planned to invest in technology adoption in 2020 changed its investment plans, again mostly downward. These changes are large economically: On average, firms which planned to invest in innovation reduced their investments in R&D by 750,000 euro, and technology adoption by 954,000 euro compared to plans. We further show that those firms which did not adjust their investment in technology were either not adversely

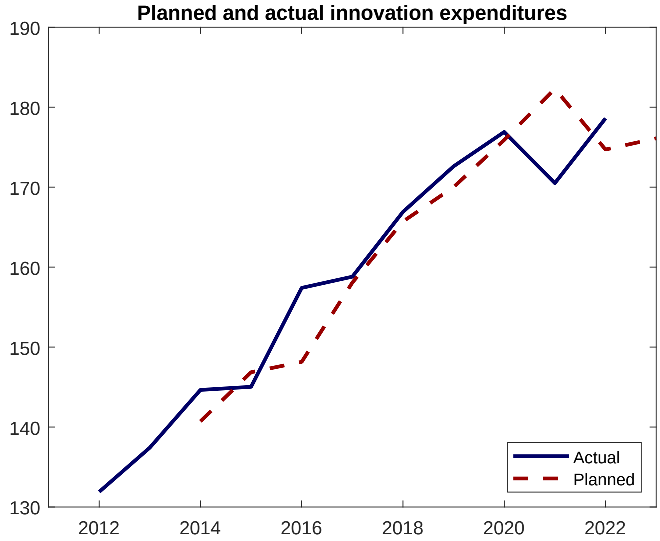


Figure 1: Pre-crisis trends in planned (red line) vs. actually realized innovation expenditures (blue line) in Germany (source: Mannheim Innovation Panel (ZEW); units: bn. euros)

affected by the crisis (25%) or if affected had sufficient financial means available (25%) which allowed them to maintain their investment in innovation at the level planned pre-crisis. Thus, typically only those firms which faced a cyclical change in their respective economic conditions adjusted their innovation investments. Moreover, our results suggest that the cut in innovation expenditure would have been more severe in the absence of sufficient financial resources, highlighting the importance of financial conditions. Our firm-level results suggest a procyclical response of TFP, driven by a procyclical decline of both investment in R&D and in technology adoption activities.

There is little evidence on the procyclicality of R&D and technology adoption, above all with respect to the latter given the lack of aggregate time series. Our results provide evidence on the procyclicality of R&D and technology adoption at the firm-level with the following main results: Firstly, we observe a pronounced degree of procyclicality both on the R&D and technology adoption margin. Secondly, we document a stronger drop in adoption expenditures, reflecting the longer-term orientation and budgeting practices of research and development compared with the more flexible of non-frontier innovation through technology adoption.

We further utilize detailed information on the causes underlying the adjustment of investment in technology. As a key driver of both the decrease in R&D and technology adoption alongside economic uncertainty emerges a cyclical drop in demand for firms' product and services. This result shows the importance of demand-side shocks in technology enhancing-investment and hysteresis effects in TFP. This firm-level evidence thus speaks in favor of spillovers from short-run aggregate demand to long-run aggregate supply, which is ruled out by assumption in standard macroeconomic models with exogenous technology stock. Our data features granular information on firm characteristics which permits us to give information on the determinants of hysteresis in TFP at the firm level. By means of this part of the analysis we aim to provide detailed information on the sources of hysteresis across the distribution of firms as well as to shed light on the relative importance of firm-level constraints in this context. These results can inform both monetary and fiscal policy and enable well-targeted macroeconomic policy effective in alleviating hysteresis effects and the long-run costs of recessions.[1]

We show that our empirical results can be rationalized by means of a New Keynesian DSGE model with endogenous TFP dynamics through technology-enhancing investment.[2] Specifically, accounting for technology growth endogenously predicts a procyclical movement of investment in R&D and technology adoption and thus procyclical TFP dynamics. In this environment transitory shocks can exert permanent effects operating through the endogeous TFP mechanism and recessions can cause permanent scars to the long-run trend via hysteresis effects in TFP. Our empirical results thus speak in favor of macroeconomic models which model technology growth and long-run trend dynamics endogenously and are inconsistent with standard models with exogenous technology.

Using our model we study in particular also a central shock from our empirical analysis, a demand shock for firms' goods and services and compare the dynamics with those from a model with exogenous technology. We show that, as documented in the data, in the model with endogenous technology transitory demand shocks affect investment in R&D and technology adoption and, over time, TFP and the long-run trend. Hence, while the shocks in themselves are transitory they exert a long-run affect to aggregate supply. These spillovers from short-run aggregate demand to long-run aggregate supply are absent in the model with exogenous technology which predicts a reversal to pre-shock trend even for large and persistent demand drops. We further show that the magnitude and the persistence of the output drop are crucial in determining the magnitude of hysteresis effects. Concentrated shocks cause less detrimental scars to long-run aggregate supply than broad-based shocks affecting the whole firm distribution. Further, transitory ("V-shape") shocks cause less deep scars than very persistent ("L-shape") shocks which induce a more pronounced drop in innovation activities. The latter emphasizes the importance of demand stabilization in this context and is suggestive that monetary policy affects aggregate output not only in the short but also long run.

Previous literature:

This paper contributes to the literature on hysteresis effects in TFP and the long-run effects of transitory shocks in this context. Evidence based on New Keynesian models with endogenous TFP mechanism estimated on aggregate time series data demonstrate that recessions can result in hysteresis effects in TFP as the latter depress investment in R&D and technological diffusion (Moran and Queralto (2018), Anzoategui et al. (2019), Bianchi et al. (2019), Elfsbacka Schmöller and Spitzer (2021)). A crisis-induced, endogenous drop in investment in innovation can help reconcile the weak recoveries following previous recessions and the simultaneously observable further deceleration of TFP during these crisis, where demand shocks emerge as important

[1] The detailed empirical analysis on the firm-level determinants is currently in progress. The corresponding results will feature in an updated paper draft.

[2] We work with a two-tier innovation structure to map the detailed information on frontier innovation through R&D versus non-frontier innovation through technology diffusion activities.

drivers of TFP in this context.[3]

There is further empirical evidence on hysteresis effects and thus the long-run effects of transitory shocks. A central result in this context are the long-run effects of contractionary monetary policy shocks as shown by Jordà et al. (2020) by means of local projections using aggregated data, which can be rationalized by means of macroeconomic models with endogenous TFP dynamics. Moran and Queralto (2018) provide further empirical evidence on hysteresis effects in TFP through a drop in technology-enhancing investment in R&D and technology adoption in response to a monetary policy shock by means of a VAR model. Amador (2022) shows hysteresis effects in both human capital and technology adoption in response to a contractionary monetary policy shock.[4] Further, recent empirical evidence demonstrates the long-run effects of fiscal policy, as studied by Cloyne et al. (2022) by means of government spending and by Antolin-Diaz and Surico (2022) for tax cuts.[5]

Furlanetto et al. (2021) provide further empirical evidence on the hysteresis effects of demand shocks in US data by means of a structural VAR model. Aikman et al. (2022) provide further evidence on hysteresis effects using aggregated data in response to both demand- and supply-driven recessions. Earlier empirical work by Barlevy (2007) shows the procyclicality of aggregate R&D. Evidence on the cyclical behavior of technology adoption are scarce due, also due to the lack of aggregate statistics. Anzoategui et al. (2019) presents empirical evidence on the procyclicality of adoption by means of a set of specific technologies. Fatás (2000) further shows the positive correlation between the persistence of output fluctuations and long-term growth rates which are inconsistent with standard models of aggregate fluctuations but can be rationalized in models with endogenous trend growth and resulting hysteresis effects.

Micro evidence on hysteresis effects in TFP is scarce at this point. This paper contributes in particular to this strand of the literature as we provide empirical evidence on the adjustment in investment in innovation in response to adverse cyclical shocks at the firm level. In particular, we establish a causal link between cyclical shifts in demand and the adjustment of investment in innovation in R&D and adoption activities at the firm level, thus providing evidence on long-run effects of transitory changes in aggregate demand. Ilzetzki (2022) shows the positive effect of large demand shocks under simultaneous capacity constraints on total factor productivity on the firm level using government purchases of aircraft production in the US during World War II. Further micro-level evidence demonstrates hysteresis effects in financially constrained firms. Huber (2018) shows that bank lending cuts reduce investment in innovation and thus future productivity using firm-level data for Germany. Duval et al. (2020) show by means of

[3]This previous literature focuses on the hysteresis effects in TFP and the downward shift in the trend path following the Great Recession in the US and the double dip recession in the euro area 2008/9 and the subsequent sovereign debt crisis. These episodes where characterized by a downward shift in real GDP compared with its pre-crisis level and a further, cyclical slowdown in TFP. Weakness of aggregate demand in the context of the crisis were identified in this literature as the key drivers of the drop in technology-enhancing investment in the context of these crisis episodes.

[4]Hysteresis in TFP changes the role and scope of monetary policy as the latter is non-neutral also over the long run in this environment. Garga and Singh (2021) derive optimal monetary policy in this environment. Benigno and Fornaro (2018) show in a theoretical framework how weak aggregate demand can lead to self-fulfilling stagnation traps at the ZLB characterized by a permanently reduced long-run growth rate. Elfsbacka Schmöller and Spitzer (2022) show that ZLB episodes are disproportionally costly under a standard Taylor rule due to hysteresis effects in TFP which can be alleviated through make-up monetary policy strategies.

[5]Elfsbacka Schmöller (2022) shows theoretically that fiscal policy has long-run effects under endogenous investment in innovation.

cross-country firm-level data that firms with more pronounced pre-crisis exposure reduced more strongly innovation activities in the global financial crisis 2008, leading to weaker productivity growth.

Lastly, as we study technology-enhancing investment and TFP in the COVID-19 crisis, this paper also contributes to the literature on the productivity and long-run growth affects of the pandemic crisis. As to historic pandemics more broadly, Jordà et al. (2022) provide empirical evidence in support of the long-term effects of such episodes. As to the COVID-19 crisis specifically, previous work studies the related immediate, i.e. short-run productivity effects. Bloom et al. (2020)) estimates TFP fell by up to 6% 2020-2021. Fernald and Li (2021) assess a downward shift in potential output relative to pre-crisis level and, further, predict that the low long-run growth trajectory which emerged pre-COVID also to prevail post-pandemic. Aksoy et al. (2022) study the longer-term effects of COVID-19 through shifts in terms of working from home.

2 Data - The Bundesbank Online Panel Firms (BOP-F)

To collect micro-level evidence on firms' investment in innovation in a recession, we introduced a special module into the regular, monthly representative survey of firms conducted by the Bundesbank - the Bundesbank Online Panel of Firms (BOP-F). The module on innovation activities was fielded in July, August and September 2021. It covers both firms' ex-ante plans before the COVID crisis emerged regarding R&D and technology adoption, respectively, for 2020 and ex-post information on their actual spending in 2020. This data permits us to identify how firms changed their plans to invest in innovation during the crisis.

Importantly, we also ask firms who adjusted their investment decisions about the reasons for this change, linked to the coronavirus pandemic. The reasons cover change in demand and supply side factors, access to financing as well as COVID-specific conditions, general economic uncertainty and others. Moreover, the firms who maintained their pre-crisis investment plans were asked to report on the underlying reasons of doing so. This provides us with further insights on the mechanism behind the innovation decisions in a recession.[6]

The BOP-F is a representative survey of firms in Germany with a least one employee, paying social security contributions, and a turnover of more than 22,000 Euro. The survey covers firms in both the manufacturing and service sector. Since July 2021, between 2,500 and 3,000 firms participated each month.[7] Our module on innovation activities was administered to a random subsample in the third quarter of 2021, resulting in a sample of slightly more than 5500 firms. We drop observations, if the firm's responses about amounts they plan to invest in innovation (both R&D and technology adoption (TA)) fall into the top 1% of the unweighted distribution, except when these firms belong to the healthcare industry or belong to the two top categories of firms with largest turnover. In total, we drop 47 observations.

[6]For more details on the questions refer to the online appendix.

[7]For more information on the BOP-F Boddin, D., M. Köhler and P. Smietanka (2022), Bundesbank Online Panel – Firms (BOP-F) – Data Report 2022-16 – Metadata Version 1, Deutsche Bundesbank, Frankfurt am Main.

Table 8 in the Appendix shows the share of firms investing in R&D at least occasionally. The overall share of firms reporting any R&D activities is at 50% (26% continuously, 24% occasionally) higher than in other surveys. The structure (occasional vs. continuous) and dynamics seem to be similar, however. The Mannheim Innovation Panel (MIP) survey e.g. indicates that in 2019 59% of firms reported to have any innovation activities over the last three years (2020: 61 percent), but only 12% reported continuous R&D activities and 9% occasional R&D activities. These numbers did not change noticeably between 2019 and 2020 (2020: any innovation activities 61% , cont.: 12% , occ.: 9%).[8] This is consistent with our finding that hardly any firm, which had not planned any R&D or technology adoption in 2019, started such activities in 2020 (see Tables 2 and 3) and that very few firms completely abandoned their plans.

Table 1: Firms by investment behavior in R&D, BOP-F

	(1) Invest in R&D continuously mean	(2) Invest in R&D occasionally mean
Invest continuously with budget	0.286	
Invest continuously w/o budget	0.714	
Invest occasionally		0.358
Do not invest typically		0.642
Observations	1818	3672

Notes: Trimmed data
Source: Forschungsdaten- und Servicezentrum (FDSZ) der Deutschen Bundesbank, BOP-F, Waves 6-8, own calculations.

Table 1 provides additional insights into how regular firms invest in R&D activities. Among the 26% of firms investing continuously in R&D (”core innovators”) the majority does so without a fixed R&D budget. The group without continuous R&D investments (”non-core innovators”) is dominated by those typically not investing in R&D at all.

Economic and institutional environment: the recession in Germany

In this paper we investigate empirically whether firms in Germany changed their R&D and technology adoption plans in 2020, when the Corona-Pandemic hit the economy. As to the general aggregate economic environment, the German economy experienced a pronounced recession starting with the outbreak of COVID-19 in 2020. The COVID-19 crisis in Germany was accompanied by comprehensive support from both monetary and fiscal policy (see Federal Ministry of Finance (2022) for a detailed list of fiscal support packages in Germany during the pandemic). The year 2020 was characterised by lockdowns, which affected the conduct of business in many sectors, in general reduced demand and high uncertainty. Up until the fourth quarter 2019 German real GDP was growing, before it dropped substantially in the first and second quarter

[8] Source: Zentrum für Europäische Wirtschaftsforschung (ZEW), 2022 - Kernindikatoren zum Innovationsverhalten der Unternehmen - Ergebnisse der jährlichen Innovationserhebung für das produzierende Gewerbe und ausgewählte Dienstleistungsbranchen in Deutschland.

of 2020. To counter the adverse effects of the pandemic, the German government put in place several programs to support businesses. As to R&D in the first year of the Corona pandemic, aggregate time-series document a decline in per capita Business Expenditure on Research and Development ("BERD") in Germany from a record high of 913 Euro to 854 Euro (-6 percent) and the European Union from 465 Euro to 456 Euro (-2 percent)[9] as well as a decline in innovation expenditure by about 3.5 percent.[10] Despite the more pronounced reduction in R&D in Germany, compared with the rest of the European Union, Germany still remained among the six countries with the highest BERD per capita in Europe.[11] In the following section, we present the results of our survey and discuss our findings.

3 Empirical Results

We first discuss the results pertaining to a qualitative assessment of firm's investment decisions: Did firms change their decisions to invest in R&D and technology adoption? And if yes, in which direction - did they increase, or decrease their investments? We also consider if firms which did not plan to invest in R&D or technology adoption before the crises, decided to engage in either.

3.1 Direction of change in investment in innovation

Table 2 and 3 provide several important facts. First, a large share of firms which planned R&D or technology adoption before the recession, changed their plans, mostly decreasing their investments: 31% of firms which planned R&D changed their investments in R&D (column 1 of Table 2), while respective numbers for technology adoption (TA) are somewhat lower at 24% of firms reporting changing their plans (Column 1 of Table 3). Second, it is remarkable that almost all of the firms which did not plan to engage in either R&D or TA in the first place, did not change their plans. This result is highly consistent among both R&D and TA activities, with 99% of firms reporting no plans also stating no investments in the respective areas.

[9]Sources: Eurostat/OECD - BERD by NACE Rev. 2 activity [RD$_{EB}ERDINDR2$].

[10]Source: Zentrum für Europäische Wirtschaftsforschung (ZEW), 2022 - Kernindikatoren zum Innovationsverhalten der Unternehmen - Ergebnisse der jährlichen Innovationserhebung für das produzierende Gewerbe und ausgewählte Dienstleistungsbranchen in Deutschland.

[11]Information based on additional Innovation and R&D indicators: https://ec.europa.eu/research-and-innovation/en/statistics/performance-indicators/european-innovation-scoreboard/eis.

Table 2: Change of Plans to invest in R&D, BOP-F

	(1)	(2)
	Planned RD	Didnt plan RD
	mean	mean
No change, RD	0.693	0.991
Increased, RD	0.062	0.009
Decreased, RD	0.245	.
Observations	2629	2182

Notes: Trimmed data, all respondents
Source: Forschungsdaten- und Servicezentrum (FDSZ) der Deutschen Bundesbank, BOP-F, Waves 6-8, own calculations.

Table 3: Change of Plans to invest in TA, BOP-F

	(1)	(2)
	Planned TA	Didnt plan TA
	mean	mean
No change, TA	0.763	0.990
Increased, TA	0.046	0.010
Decreased, TA	0.191	.
Observations	2934	1846

Notes: Trimmed data, all respondents
Source: Forschungsdaten- und Servicezentrum (FDSZ) der Deutschen Bundesbank, BOP-F, Waves 6-8, own calculations.

It also is of interest that, generally speaking, firms' adjustments concerning investments in R&D are quite alike to the adjustments concerning TA. Still, a larger share of firms planned to engage in technology adoption before the crises, and a larger share of firms which planned TA decide to stick with their plans (76% of firms which planned TA stuck with their plans, while for R&D this is 69%). However, it should be noted, that very few firms planed only one type of innovation activity (R&D or TA) exclusively. Table 11 in the Appendix attest to the fact that most of the firms in our sample planned both R&D and technology adoption (about 50%), and a large share of the firms did not plan any investments in either of the two innovation activities for the year 2020. While only 8% of firms report to have planned R&D only, about 15% of firms planned to invest in technology adoption only. At the same time, a very small share of firms switches from one type of investment to another (columns 1 and 2 Table 11); a higher but still small proportion of firms increases one type of investment if planned both.

Another useful distinction is between core and non-core innovators. As introduced in the Table 1, core innovators are the firms which invest in R&D regulary, with budget or without. Non-core innovators, in turn, invest either occasionally in R&D, or do not invest typically. This allows us to better fence out the differences in investments with respect to innovation of the firms which regularly engage in frontier research, and otherwise.

Indeed, from Table 4 we observe a clear difference between core and non-core innovators: Core innovators are more likely to adjust their research and development activities, with 34% of core innovators reporting a change in R&D, vs. 27% of non-core innovators. This observations will be more important when linked to the amounts invested (which is much higher for core innovators, as we will show in the subsequent sections). However, when looking at the qualitative indicators in Table 5, the differences between core and non-core innovators are smaller when it comes to TA, mostly in the share of firms which decreased their expenditure on technology adoption comparing with plans (21% of core innovators, vs. 17% of non-core innovators). In summary, it looks like the firms with the more dedicated innovation activities, i.e. the core innovators, adjusted their plans more often than the less innovation active firms (non-core).

Table 4: Change of Plans to invest in R&D, by core and non-core innovators

	Planned R&D		Didnt plan R&D	
	core	non-core	core	non-core
	(1)	(2)	(3)	(4)
No change, RD	0.664	0.729	0.946	0.994
Increased, RD	0.077	0.043	0.054	0.006
Decreased, RD	0.259	0.228	.	.
Observations	1455	1171	148	2028

Notes: Trimmed data
Source: Forschungsdaten- und Servicezentrum (FDSZ) der Deutschen Bundesbank, BOP-F, Waves 6-8, own calculations.

Table 5: Change of Plans to invest in TA, by core and non-core innovators

	Planned TA		Didnt plan TA	
	core	non-core	core	non-core
	(1)	(2)	(3)	(4)
No change, TA	0.732	0.787	0.985	1.000
Increased, TA	0.054	0.040	0.015	.
Decreased, TA	0.214	0.173	.	.
Observations	1296	1634	259	1582

Notes: Trimmed data
Source: Forschungsdaten- und Servicezentrum (FDSZ) der Deutschen Bundesbank, BOP-F, Waves 6-8, own calculations.

While we argue that 30% of firms changing their decisions to invest in innovation comparing to the plans is a large and meaningful effect, it is necessary that we address the 70% of the firms which did not change their plans (conditional on having them).[12]

[12]Given the very small propensity to start investing in either R&D or TA if no previous plans existed, in the

As a part of the survey, we asked the firms who reported no change in their plans about the reasons for this choice. The results are presented in the Figure 2. Essentially, this information demonstrates that 46% of firms did not perceive a change in economic conditions, in other words, were not hit by a shock. Another 33% of the firms report that the reason for sticking with their investment in innovations plans was availability of financial resources, even if they have faced change in economic conditions. These results are important as they strongly suggest that the drop in investment in innovation could have been much more pronounced if financing conditions would not have been this favorable or if more firms had been adversely hit by the crisis.

Figure 2: Reasons if no change undertaken, given non-zero plans

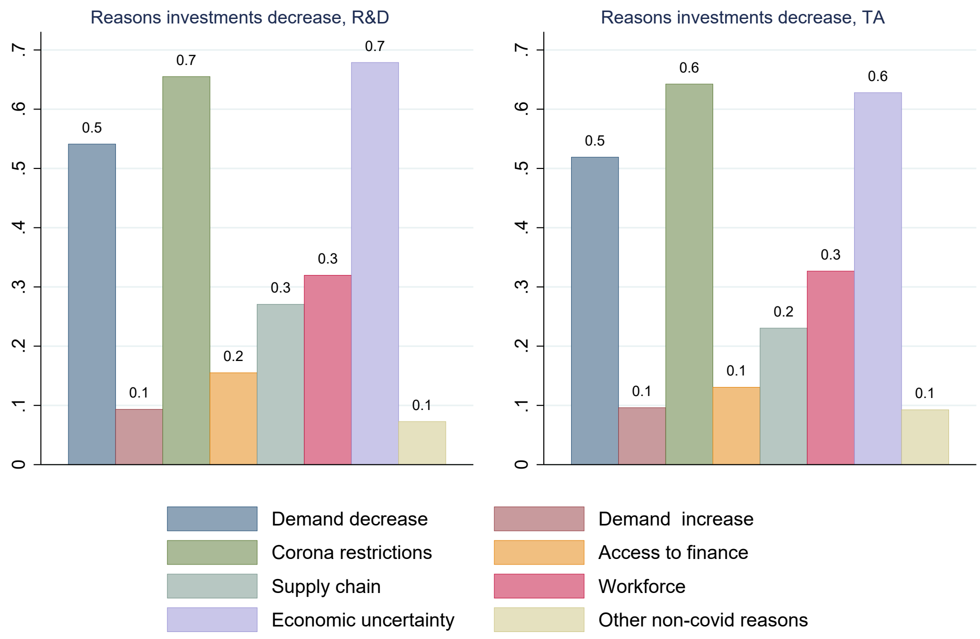
Notes: Conditional on having plans to invest in R&D or TA

Source: Forschungsdaten- und Servicezentrum (FDSZ) der Deutschen Bundesbank, BOP-F, Waves 6-8, own calculations.

Remarkably, these findings are very consistent with the reasons for firms which have adjusted their technology-enhancing spending: Financial conditions seem to have been favorable during the COVID recession and therefore were rarely a reason for decreasing investment in innovations. This is evident from Figures 3 and 4, which show that only 20% of firms which decreased R&D investments and 10% of firms which decreased spending on technology adoption stated that it was due to the financial conditions. This lends the argument, that in the absence of the large and effective fiscal and monetary support, we would have observed yet more pronounced changes in innovation activities. At the same time, even less firms (10% overall) increased their spending on innovation as response to changes in the access to finance, which in turn suggests that in crisis access to finance is important to prevent drop in investments, but does not appear to be a sufficient condition to stimulate innovation and technology growth.

further analysis we will mostly concentrate on firms which had plans to invest in at least one type of innovations in the year 2020.

Figure 3: Reasons for firms decreasing investments in R&D and TA, by investment type



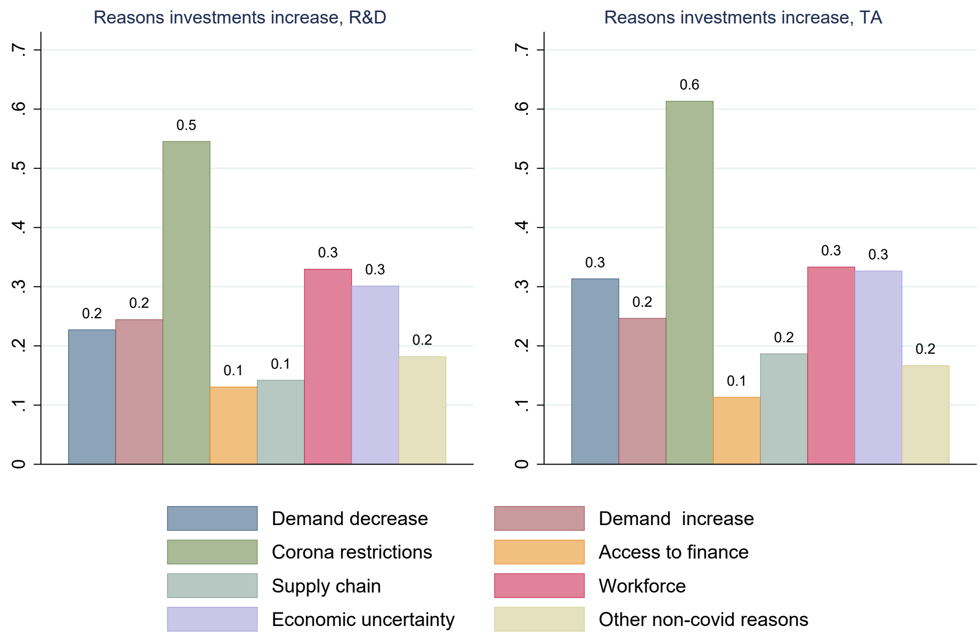
Notes: Trimmed data. Each category is counted as 1 if respective sub-categories were selected by a respondent at least once, and zero otherwise

Source: Forschungsdaten- und Servicezentrum (FDSZ) der Deutschen Bundesbank, BOP-F, Waves 6-8, own calculations.

Overall, the figures above demonstrate that reasons for adjusting investment in innovation are highly similar for R&D and technology adoption, which is in line with theoretical view from macroeconomic models with endogenous TFP mechanism that investment in frontier-innovation and technological diffusion strongly co-move and are driven by similar shocks (as shown by Anzoategui et al. (2019) for the US and Elfsbacka Schmöller and Spitzer (2021) for the euro area). Concerning the main reasons for decrease in innovation spending, changes in demand was a predominantly important factor (for 50% of the firms), together with COVID-related administrative restrictions (60%-70% of the firms) and general economic uncertainty.

For investment increase, though only a small share of firms have chosen to do so, corona restrictions appear to be the single driving force for firms investing both in R&D (50%) as well as in technology adoption, with larger effect for latter (60%). Both demand decrease and demand increase were important for about 20%-30% of firms (again, larger weight for technology adoption), whereas changes in workforce and general economic uncertainty have played a role for 30% of firms. These findings are in line with reports of some positive effect of the corona crisis on certain segments of innovation, in particular through technology adoption, though this effect remains limited to a small share of firms.

Figure 4: Reasons for firms increasing investments in R&D and TA, by investment type



Notes: Trimmed data, each category is counted as 1 if respective sub-categories were selected by a respondent at least once, and zero otherwise

Source: Forschungsdaten- und Servicezentrum (FDSZ) der Deutschen Bundesbank, BOP-F, Waves 6-8, own calculations.

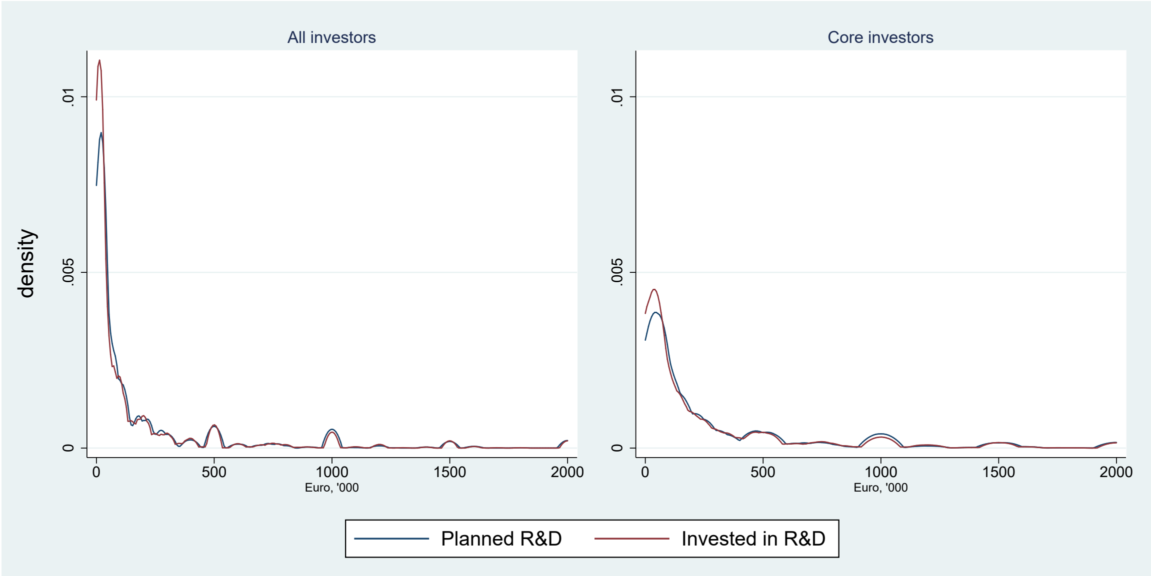
In the next section we discuss the intensive margin, e.g. changes in amounts invested in R&D and technology adoptions.

3.2 Magnitude of the change in investment in innovation

Figure 5 and Figure 6 demonstrate several empirical facts. First, investment patterns are similar for both R&D and technology adoption decisions. Second, there is a large mass of firms which invest relatively small amounts, while the distributions show very long "tails" - meaning a very large dispersion of amounts invested. Third, a larger share of core investors spends larger amounts on both R&D and technology adoption, than non-core investors (Fig. 5 and Fig. 6, right panel).

Comparing plans and realisations, R&D investors (including core investors who engage in technology adoption) appear to adjust their investments by more. Specifically, a larger share of R&D investors (Fig. 5 and Fig. 6, left panel) report actual investments to be below 100 000 euro. This picture is consistent for the core investors who engage in technology adoption (Figure 6, right panel).

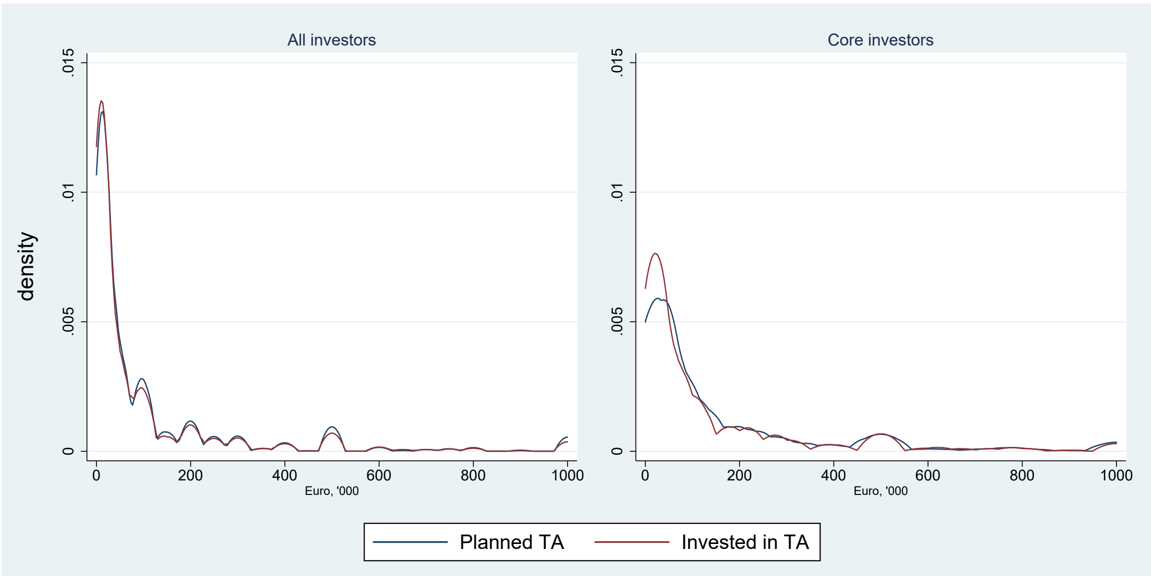
Figure 5: R&D plans and realizations



Notes: Conditional on having plans to invest in R&D

Source: Forschungsdaten- und Servicezentrum (FDSZ) der Deutschen Bundesbank, BOP-F, Waves 6-8, own calculations.

Figure 6: TA plans and realizations



Notes: Conditional on having plans to invest in TA.

Source: Forschungsdaten- und Servicezentrum (FDSZ) der Deutschen Bundesbank, BOP-F, Waves 6-8, own calculations.

Tables 6 and 7 report some moments of the distribution of planned investments in R&D and technology adoption, as well as the distribution of changes. Again we see a striking similarity between changes to both types of innovations. The planned amounts, the median increase and to a lesser extend the median and mean decrease are of a similar magnitude.

On average the reduction for both technology adoption and R&D compared to pre-crisis plans was slightly less than 50% for all firms with plans to invest.[13] For core innovators, the reduction in technology adoption was even higher (66%), while the average reduction in R&D activities lower (30%). This lends empirical support to theoretical predictions and to prior empirical studies for specific technologies (as shown in Anzoategui et al. (2019)), that investment in technology adoption is more procyclical than R&D.

Table 6: Investments in R&D, conditional on having plans, by innovator type, '000 euro

	(1) All					(2) Core investors				
	p10	p50	p90	mean	count	p10	p50	p90	mean	count
Planned R&D, 000s euro	5	50	1400	1955	2664	10	100	3000	3088	1477
Decrease R&D, 000s euro	-700	-30	-5	-750	644	-1000	-50	-7	-966	377
Increase R&D, 000s euro	5	33	338	179	162	5	50	499	174	112
Change in R&D, 000s euro				-173	2629				-237	1455

Notes: The data presents input by firms, amounts in '000 euro, rounded to full numbers, trimmed at at top 1% of planned amounts. Mean change in R&D includes zeros for firms with no change.
Source: Forschungsdaten- und Servicezentrum (FDSZ) der Deutschen Bundesbank, BOP-F, Waves 6-8, own calculations.

Table 7: Investments in TA, conditional on having plans, by innovator type, '000 euro

	(1) All					(2) Core investors				
	p10	p50	p90	mean	count	p10	p50	p90	mean	count
TA investments: 000s planned	5	40	1000	2039	2964	10	80	2000	2565	1317
Decrease TA, 000s euro	-650	-30	-4	-954	559	-1000	-50	-5	-1687	276
Increase TA, 000s euro	5	20	225	144	135	5	50	390	199	70
Change in TA, 000s euro				-175	2932				-349	1295

Notes: The data presents input by firms, amounts in '000 euro, rounded to full numbers, trimmed at at top 1% of planned amounts. 2 extreme outliers are dropped due to data protection issues. Mean change in technology adoption includes zeros for firms with no change.
Source: Forschungsdaten- und Servicezentrum (FDSZ) der Deutschen Bundesbank, BOP-F, Waves 6-8, own calculations.

While the changes for the large majority of the firms do not seem to be so large in absolute terms (though large in relative), there are long tails in the distributon, and these firms plan to invest a lot and accordingly adjust their plans by sometimes very large amounts. This is evident from the top 10 and bottom 10 percentiles for R&D spending and especially for technology adoption. While median decrease is about 30 000 euro for both types of innovations, the mean decrease

[13] A relatively small share of firms completely erases their spending on either R&D or technology adoption. Also, core investors are less likely to do this (43 and 42 firms for R&D and TA respectively), comparing to non-core investors (98 and 105 firms for R&D and technology adoption respectively)

for R&D is 750 000 euro, and for technology adoption it is close to 1 mln. euro. This is due to a small number of firms with very large innovation budgets, and - subsequently - large changes. It is not unlikely that investments in technology adoption can represent very large amounts (in case of patent purchases, or equipment etc.) and also could be easier postponed or cancelled than research and development activities, which might require more complex processes and are subject to long-term orientation, including planning and budgeting.

4 Investments in innovations and recession: Regression analysis

In the following we discuss the relations between the firm's decisions to decrease investments in R&D or TA and the (strength) of recession impact as well as expectations about demand and access to financing.

To do so, we link the customized survey on firm's investment decisions which we ran in the third quarter of 2021 in BOP-F, with the survey responses of the same firms in June-July 2020. The timing here is of vital importance: While we learn about the changes in investment decisions of the firms **ex-post** (after the recession shock is mostly over), we link these decisions with firm's perceptions about crises impact and expectations about the situation in the next half of year **in the middle of the crises**, which coincides with the half-year timing, when the decisions to continue with investments or not were likely made.

Table 8 presents results of the regression analysis. The outcome is a binary variable, which is equal to 1 if a firm has reported that it has invested lower amounts than planned in R&D in the year 2020. Given the decision process, we use the heckmann probit model for estimation, where the selection criteria is the initial plans to invest in R&D in 2020. We report average marginal effects after heckprobit.

The main explanatory variables are the following:

1. Firm's report whether production or business activity have decreased as a result of the coronavirus pandemic. This is an indicator variable equal to 1 if there was a negative impact, and 0 otherwise.

2. Firm's report on the **magnitude** of the production or business activity decrease as a result of the coronavirus pandemic. Given in percents of production (business activity).

3. Indicator variables equal to 1 if a firm expects decrease in demand, problems with access to financing or closures or work restrictions due to coronavirus pandemic during the next six months.

Additional controls include firm's employee count, turnover, location (of the headquarters) and the main industrial sector of firm's operations.

Table 8: Decreased investments in R&D, effect of recession and expectations

	Recession impact		Recession intensity		Expectations	
	1	2	3	4	5	6
Production decreased due to recession	0.506***	0.426***				
	(0.079)	(0.086)				
Production decrease due to recession, pct			0.006***	0.006***		
			(0.001)	(0.002)		
Expect problems with demand					0.438***	0.346***
					(0.083)	(0.091)
Expect problems with financing					0.256**	0.258**
					(0.117)	(0.123)
Expect problems due to covid restrictions					-0.026	0.032
					(0.086)	(0.094)
Covariates	No	Yes	No	Yes	No	Yes
N observations	1345	1337	1215	1207	1328	1321

Notes: Marginal effects after heckmann probit. Exclusion criteria is having planned R&D. Report on investments decisions of the firms is collected in the 2021, July-September. Information on recession impact and expectations about next 6 months are collected in June-July 2020. Recession intensity is measured as impact of the recession on production or business activity in percent.
Source: Forschungsdaten- und Servicezentrum (FDSZ) der Deutschen Bundesbank, BOP-F, Waves 6-8, own calculations.

The results are quite striking evidence of the link between recession and the decisions to decrease investmetns in R&D. If a firm's business activity has been hit by recession during the first half of 2020, it is 50% more likely to reduce the investments in R&D (columns 1, table 8). This effect decreases somewhat - to 42 % - controlling for firm's general characteristics (column 2). More detailed measurement of the recessionary impact - the percent decrease in production activity due to recession - delivers result of a similar magnitude: 1% decrease in production is related to 0.6% increase in the probability that firm will decrease it's investment in R&D (columns 3 and 4)

While the first two rows of the table 8 present the effect of the *past* recession effect on the investment decisions, the rows 3 to 5 show how *expectations* influence these decisions. If a company expects issues with demand over the next six months, it is 44% more likely to decrease the investments in R&D - the effect decreases somewhat, to 35% controlling for firm's characteristics.

Expectations of financing issues have also large and significant impact on the probability to decrease investments in R&D - about 26%. (row 4, column 5 and 6)

At the same time, coronavirus-related administrative restrictions do not appear to have any effect on the decision to decrease the R&D (row 5, column 5 and 6)

It is important to note, that these effects are rather stable when including firm's standard characteristics, such as size and industry (comparing columns pairwise, with and without covariates). This suggests, that the effect of recession is relatively independent of the size or industry.

Finally, these results are strikingly similar if we consider decisions to decrease investments in technology adoption (Table 9), though the effects of recession on production decrease are somewhat smaller (around 30%, see columns 1 and 2).

Table 9: Decreased investments in TA, effect of recession and expectations

	Recession impact		Recession intensity		Expectations	
	1	2	3	4	5	6
Production decreased due to recession	0.381***	0.332***				
	(0.080)	(0.085)				
Production decrease due to recession, pct			0.007***	0.006***		
			(0.002)	(0.002)		
Expect problems with demand					0.342***	0.272***
					(0.085)	(0.093)
Expect problems with financing					0.235*	0.284**
					(0.122)	(0.128)
Expect problems due to covid restrictions					0.089	0.130
					(0.088)	(0.092)
Covariates	No	Yes	No	Yes	No	Yes
N observations	1323	1315	1155	1184	1306	1299

Notes: Marginal effects after heckmann probit. Exclusion criteria is having planned TA. Report on investments decisions of the firms is collected in the 2021, July-September. Information on recession impact and expectations about next 6 months are collected in June-July 2020. Recession intensity is measured as impact of the recession on production or business activity in percent.
Source: Forschungsdaten- und Servicezentrum (FDSZ) der Deutschen Bundesbank, BOP-F, Waves 6-8, own calculations.

5 Theoretical mechanism

To shed light in the theoretical mechanisms underlying our empirical results we study the related macroeconomic dynamics by means of a macroeconomic model with endogenous investment in innovation and endogenous trend dynamics and compare the related implications with those in standard models with exogenous technology. We describe in detail the endogenous trend dynamics in section 5.1.2 and show for brevity the more standard medium-scale DSGE model features in appendix A.3.

5.1 Model

We study the macroeconomic dynamics of the key driving shocks from our empirical analysis from the perspective of a model with endogenous technology dynamics. The main model framework represents a medium-scale New Keynesian DSGE model as in Christiano et al. (2005) and Smets and Wouters (2007). Differently to standard models, the model features endogenous trend growth: investment in technology generates innovation which leads to an expansion in the varieties of intermediate goods as proposed by Romer (1990).[14]

5.1.1 New Keynesian DSGE side

As the DSGE model side of the theoretical framework is standard we show for brevity the detailed model representation in appendix A.3. We present in detail the technology growth mechanism as it is central for the rationalization of our empirical results (see section 5.1.2). Competitive final good producers set prices subject to Calvo price and wage rigidities. Monetary policy is set by means of an inertial Taylor rule which targets inflation and an output target. Final good producers are monopolistically competitive and use intermediate goods as inputs. They set prices subject to nominal frictions. Intermediate goods are expanding in varieties and are produced by monopolistically competitive producers. Capital producers transform final output to physical capital and are subject to adjustment costs. A continuum of households supply monopolistically labor and, as in Erceg et al. (2000), a large number of competitive employment agencies transforms specialized labor to a homogeneous input L_t. Households maximize utility subject to a standard budget constraint. Both wages and prices are subject to indexation.

5.1.2 Endogenous Growth Mechanism

In our data set we can distinguish between investment in R&D and investment in the adoption of new technologies. This distinction is important as these different margins of innovation investment affect the technology stock directly through the technological frontier or through the technological diffusion margin. This difference is mapped to the model by means of a two-tier innovation process, as proposed by Comin and Gertler (2006). Specifically, technology growth occurs through research and development and technology adoption. R&D investment generates new innovations, increasing the total technology stock Z_t and the technology frontier. In order for new technologies to generate measurable increases in total factor productivity firms have to adopt them which requires costly investment in technology adoption. The respective stock of adopted technologies is denoted by A_t. The aggregate production function can be represented as

$$Y_t = \theta_t A_t^{\frac{1}{\vartheta-1}} K_t^{\alpha} L_t^{1-\alpha} \tag{1}$$

[14]The theoretical framework is based on the model proposed by Moran and Queralto (2018) which studies the long-run effects of monetary policy and is also closely linked to earlier work which introduces endogenous TFP using the mechanism by Comin and Gertler (2006) (see for instance Anzoategui et al. (2019) and Elfsbacka Schmöller and Spitzer (2021)).

where $A_t^{\frac{1}{\vartheta-1}}$ captures the endogenous component of total factor productivity and θ_t the standard technology shock.[15]

5.1.3 R&D sector: frontier innovation

Technology growth occurs through expanding varieties of intermediate goods as in Romer (1990). Growth in the technology frontier is generated through investment in resarch and development. Innovators sell the right to use a newly invented technology to the adoption sector (section 5.1.4) which converts new innovations into technologies usable in production. Z_t denotes the technology frontier at time t which faces obsolescence at the exogenous rate $1-\phi$. The technology stock thus follows the law of motion

$$Z_{t+1} = \phi Z_t + \varphi_t X_t \tag{2}$$

and thus represents the sum of newly invented technologies $\varphi_t X_t$ and of non-obsolete technologies from the previous period ϕZ_t. Further, new technologies are created by means of the innovation production technology by innovator i

$$\varphi_t X_t^i. \tag{3}$$

X_t^i represents R&D investment by innovator i, denoted in final output units and for $\varphi_t = \frac{\chi Z_t}{Z_t^{\zeta} X_t^{1-\zeta}}$, where the total R&D investment in the economy equals to $X_t = \int_i X_t^i di$. The innovation process thus features a positive spillover from the aggregate stock of technologies Z_t to the productivity of an individual innovator. The R&D process is further subject to an externality from aggregate R&D efforts, where $\frac{1}{Z_t^{\zeta} X_t^{1-\zeta}}$ and $0 < \zeta < 1$ denotes the R&D elasticity of the aggregate creation of new technologies. The latter assumption ensures stationarity. The R&D efficiency parameter χ is set to capture the long-run growth rate on the balanced growth path. J_t denotes the value of an unadopted technology, i.e. of a technology which has been created but not yet adopted in production through costly technology adoption. Technologies created at time t become ready to use from the subsequent period onward. The optimization problem of innovator i can be summarized as

$$\max_{\{X_{i,t+j}\}_{j=0}^{\infty}} \mathbb{E}_t \left\{ \sum_{j=0}^{\infty} \Lambda_{t,t+1+j} \left[J_{t+1+j} \varphi_{t+j} X_{i,t+j} - \left(1 + f^x \left(\frac{X_{i,t+j}}{X_{i,t+j-1}}\right)\right) X_{i,t+j} \right] \right\},$$

where $\Lambda_{t,t+1+j}$ denotes the discount factor of the household. R&D is subject to adjustment costs modeled by means of the convex function $f^x(\cdot)$ with the following properties. On the balanced growth path holds $f^x\left(\frac{\bar{X}_{t+1}^i}{\bar{X}_t^i}\right) = f^{x\prime}\left(\frac{\bar{X}_{t+1}^i}{\bar{X}_t^i}\right) = 0$, where $\frac{\bar{X}_{t+1}^i}{\bar{X}_t^i} = 1 + g$. g denotes the long-run growth rate of R&D investment and hence of TFP and aggregate output. Assuming symmetry and dropping subscript i the corresponding optimality condition equates the marginal costs from

[15] Total factor productivity in this model consists hence of the combination of the endogenous trend component A_t and the conventional technology shock θ_t.

research and development to the expected gains

$$\mathbb{E}_t\left(\Lambda_{t,t+1}J_{t+1}\varphi_t\right)=\Delta f^x \tag{5}$$

for $\Delta f^x=1+f^{x\prime}\left(\frac{X_t}{X_{t-1}}\right)\frac{X_t}{X_{t-1}}+f^x\left(\frac{X_t}{X_{t-1}}\right)-\mathbb{E}_t\,\Lambda_{t,t+1}f^{x\prime}\left(\frac{X_t}{X_{t-1}}\right)\left(\frac{X_t}{X_{t-1}}\right)^2$. Innovation at time t , i.e. the creation of new technologies, can be derived from $V_t=\int_i V_t^i di=\chi Z_t^{1-\zeta}X_t^{\zeta}$, where ζ is the elasticity of innovation V_t to aggregate R&D investment. The rate of growth of the technology frontier $\frac{Z_{t+1}}{Z_t}$ can be derived as $\phi+\chi\left(\frac{X_t}{Z_t}\right)^{\zeta}$. This shows that the long-run growth rate of innovation is endogenous in this framework, i.e. upward shifts in the ratio $\frac{X_t}{Z_t}$ generate permanent changes in the long-run growth rate at the BGP.

5.1.4 Technology adoption: diffusion of new technologies

Newly created technologies by R&D do not generate instantaneous TFP increases as they first have to diffuse to the wider economy which occurs through technology adoption at the firm level. This assumption generates realistic adoption lags with respect to the diffusion of new technologies. We model the technology adoption decision by means of a competitive adoption sector.[16] λ_t denotes the probability of successful adoption at time t, where the adoption probability is increasing in E_t, i.e. adoption expenditures. Investment in adoption is subject to adjustment costs and the technology adoption process requires specialized input E_t, i.e. equipment, which is converted from final output purchased at price Q_t^a. The technology adoption probability λ_t is an increasing function in the investment in adoption and described by the functional form

$$\lambda_t\left(E_t^i\right)=\kappa_\lambda\left(\frac{X_t}{A_t}\right)^{\eta}\left(E_t^i\right)^{\rho_\lambda}. \tag{6}$$

The adoption parameters are $\kappa_\lambda>0$, $0<\eta<1$ and $0<\rho_\lambda<1$. The adoption probability is thus increasing and concave in the adoption investment. The adoption rate entails a spillover term from aggregate spending on R&D X_t.[17] Technology adopters purchase the rights to use an unadopted technology from the R&D sector at competitive price J_t. The value of an adopted technology is described by

$$H_t=\Pi_t+\phi\mathbb{E}_t\left(\Lambda_{t,t+1}H_{t+1}\right). \tag{7}$$

The technology adoption choice can be derived as

$$J_t=\max_{E_t^i}-Q_t^aE_t^i+\phi\mathbb{E}_t\left\{\Lambda_{t,t+1}\left[\lambda_t\left(E_t^i\right)H_{t+1}+\left(1-\lambda_t\left(E_t^i\right)\right)J_{t+1}\right]\right\}. \tag{8}$$

[16] In doing so we can model diffusion endogenously while at the same time maintaining tractability, which simplifies aggregation. The latter is the case as the adoption probability is identical for each technology which does not require to track the fraction of firms which have adopted the respective technologies.

[17] The spillover term is adjusted for A_t for stationarity purposes. The spillover captures the property of aggregate R&D efforts exercising a positive effect on the probability of adopting new technologies as, for example, the adoption sector is learning from research and development activities.

Hence, adopters equate the costs related to adoption to the respective expected gains, which is the probability weighted sum of the value of unadopted and adopted technologies. As adoption effort will be identical across technologies ($E_t^i = E_t$), subscript i can be dropped and the optimality condition for adoption follows as

$$\rho_\lambda \kappa_\lambda \phi \left(\frac{X_t}{A_t}\right)^\eta \mathbb{E}_t \left[\Lambda_{t,t+1} \left(H_{t+1} - J_{t+1}\right)\right] = Q_t^a E_t^{1-\rho_\lambda}. \tag{9}$$

Aggregate adoption investment can be derived as the product of the investment in technology adoption E_t and the stock of unadopted technologies $(Z_t - A_t)$, i.e. $(Z_t - A_t) E_t$.

Law of motion for TFP:
The law of motion for adopted technologies and hence endogenous total factor productivity follows as the sum of the surviving adopted technologies from period and the newly adopted technologies respectively from time t

$$A_{t+1} = \phi \left[A_t + \lambda_t \left(Z_t - A_t\right)\right]. \tag{10}$$

For comparison, in the reference framework with exogenous technology, we assume that TFP grows at an exogenous rate.[18]

5.2 Transmission mechanisms of main shocks

We show in this section that while our empirical results contradict standard models with exogenous technology, they can be rationalized by means of a class of models with endogenous innovation choice and TFP dynamics, such as the model presented in section 5.1. This section further aims at showing the main macroeconomic dynamics in response to the most important shocks identified in our empirical analysis and in this context also to provide insights on the role of the underlying recession dynamics in determining the magnitude of hysteresis effects.

5.2.1 The long-run effect of demand shocks

Our empirical results emphasized the importance of cyclical downward shifts in demand for the products and services of firms in their choice to reduce their spending on R&D and technology adoption respectively. Figure 8 shows the macroeconomic dynamics in response to a transitory shock to demand for firms' output.[19] In the baseline scenario (blue line), the response to the adverse demand shock consumption, capital investment and output fall. The drop in the demand for firms' products lowers the expected payoff of R&D relatively to the cost of investment (see equ. 5). In response, firms reduce their investment in research and development, which results in a slowdown in the technological frontier. Moreover, the drop in demand generates

[18] When comparing models with endogenous and exogenous technology we work with models with identical long-run, i.e. BGP growth rates and also otherwise identical calibrations to ensure comparability.

[19] This shock is implemented by means of a preference shock which transitorily reduces consumption and increases savings by households.

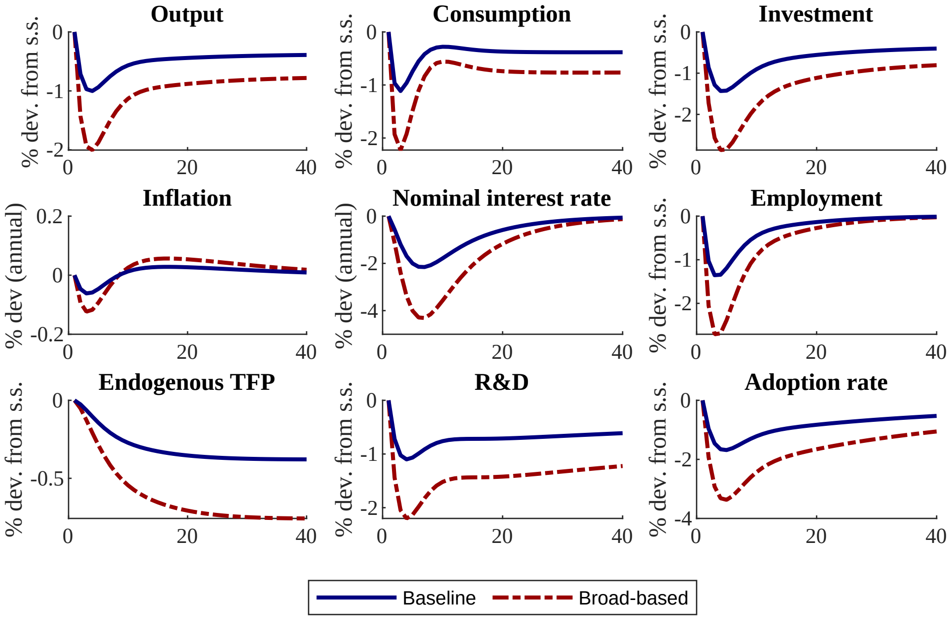


Figure 7: Macroeconomic dynamics under a contractionary demand shock

Note: comparison of baseline (blue line) and broad-based scenario in which a higher share of firms is exposed to a drop in demand (red line).

a downward adjustment in technology adoption investment as the payoff from producing using a new technology decreases relatively to the cost of technology adoption investment (equ. 9). As implied by our empirical results, technology adoption declines more strongly procyclically in response to the change than R&D. These shifts in technology-enhancing investment generate a pronounced decline in both frontier innovation and technological diffusion activities which depresses technology growth and results in a permanent drop in TFP and thus the long-run trend relatively to its pre-shock path.

The presented dynamics stand in sharp contrast to the predictions of standard macroeconomic models with exogenous technology which assume that technological investment and hence TFP are uninfluenced by short-run, transitory shocks to demand. These models would predict that technology-enhancing investment is unaffected by the transitory shock to demand. The endogenous response in TFP would thus be absent and transitory shifts in demand would exert no repercussions to long-run aggregate supply. Hence, after the shock has faded out, aggregate output would revert to its initial trend path. Under exogenous TFP, there is thus no role for hysteresis effects in response to demand shocks, which can not be reconciled with our empirical results.

Role of extent of shock-exposure at the firm level

We consider next a broad-based demand shock (red line) which captures the case in which a larger number of firms faces an adverse shock to demand. We observe the following key differences relatively to our baseline results. The more far-reaching demand shock results in a more pronounced fall in output in response to the shock and, crucially, as more firms cut their investment in technology-enhancing investment in R&D and technology adoption, a stronger deceleration in both the technological frontier and the diffusion of technologies. This results in an amplification of the procyclical drop in technology growth and TFP, subject to amplified long-run trend losses. This emphasizes that the extent of hysteresis effects in TFP are increasing in the strengths of the drop in demand. Hence, in particular recessions in which the fall in demand is pronounced in terms of intensity and/ or the share of firms exposed to the shock are prone to pronounced hysteresis effects and long-run scars to aggregate output.

5.2.2 The role of shock persistence: V-shape vs. L-shape

The data underlying our empirical analysis stem from a recession episode in which the drop in aggregate output was particularly abrupt and deep but in comparison to previous crises, such as the Great Recession, relatively short-lived. We proceed next to studying the implications of the persistence of the underlying shocks in this respect.[20] To demonstrate the effect of the persistence and the overall dynamics of the underlying shocks we compare the macroeconomics dynamics in which the underlying driving shock is strong on impact but short-lived ("V-shape", blue line) compared with a scenario in which the shock is less pronounced on impact but more protracted ("L-shape", red line). Our simulations show that under a more prolonged shock, the intensity in the reduction in both R&D and technology adoption investment is more pronounced. This is the case as agents factor in in their investment choice for both margins of innovation respectively the future payoffs from undertaking such investment. If the drop in demand is considered rather transitory, it will reduce the payoff from investing in innovation less strongly than an adverse demand shock which weighs on the gains from innovation for an extended period of time, which triggers a stronger drop of technology-enhancing investment, resulting in an amplification of hysteresis effects in TFP.

Linking these results to our empirical findings thus further also suggests that a longer-lived recession in which underlying driving shocks are more persistent - all other things equal - are subject to a more intense drop in investment in innovation and thus to an intensification of demand-supply spillovers. Our results for the most recent crisis may thus be considered a relatively conservative estimate of the extent of hysteresis effects in TFP. Similarly, the recent crisis has been met by comprehensive support from monetary and fiscal policy, which is from the lens of both our empirical and theoretical analysis likely to have prevented a yet stronger amplification of the drop in investment in innovation and of of hysteresis effects (see also Figure 1 for a comparison of actual investment in innovation versus investment planned pre-crisis).

[20] In this scenario we focus for brevity on the demand-shock scenario but we could in future work also extend our analysis to other key shocks identified in the empirical analysis.

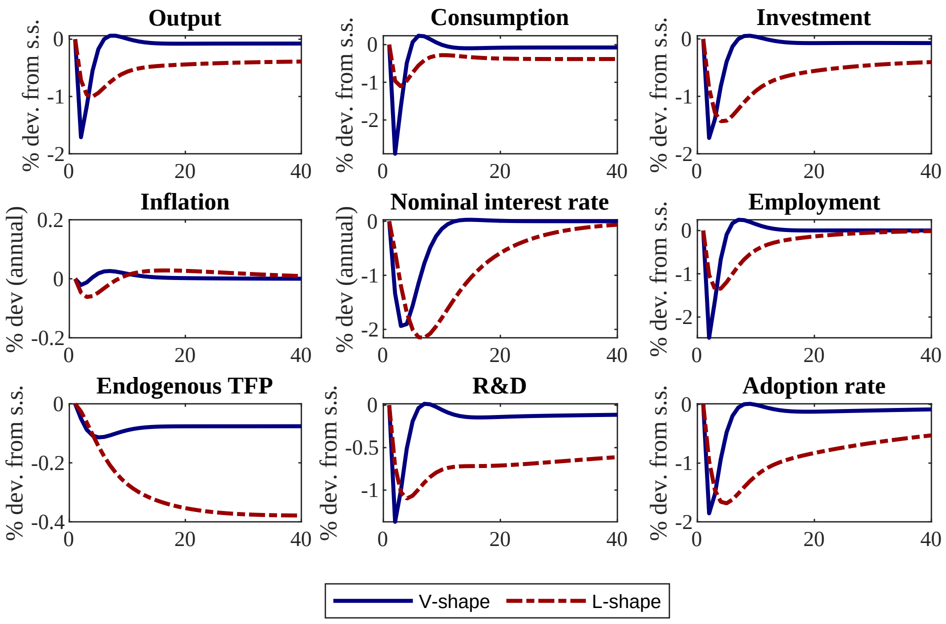


Figure 8: Magnitude of hysteresis effects (V-shape vs. L-shape)

5.2.3 Mechanisms underlying other key driving shocks

This section studies the role of further driving shocks identified as important in our main analysis, including the role of uncertainty and COVID-19 related special effects (currently in progress and will be presented in an updated paper draft).

5.3 Discussion: implications for modelling and policy

In this section (currently in progress) we discuss the implications of our empirical and theoretical results for macroeconomic modeling in particular with respect to key concepts such as potential output and output gap measures. We further discuss the implications for monetary and fiscal backdrop both against the implied signals as to measures of economic slack as well as with respect to the role and design of macroeconomic policy in preventing hysteresis effects and long-run scars of recessions.

6 Conclusion

We provide empirical evidence on changes in firms' technology-enhancing investments during a crisis by means of a large, representative survey of German firms and connect it to hysteresis effects in total factor productivity. Our results stand in contrast to the assumptions underlying standard macroeconomic models in which cyclical fluctuations are modeled around a fixed, exogenously given long-run trend. Specifically, 25% of firms cut their investment in R&D and 20%

in technology adoption respectively. We further show that these reductions in investment in innovation are large and economically meaningful, with technology adoption subject to stronger decreases which points to stronger procyclicality of technology diffusion. Further, survey based information suggests that these reductions are causally linked to the crisis episode. Moreover, we find that demand shocks constitute a main driver underlying firms' downward adjustment in innovation expenditure, suggestive of spillovers from short-run aggregate demand to long-run aggregate supply. By means of the rich firm-specific information we pin down the determinants of hysteresis at the firm level which can guide macroeconomic policy as to effective and well-targeted monetary and fiscal tools to alleviate the long-run scars of recessions. We rationalize our empirical findings in a New Keynesian DSGE model with endogenous technology-enhancing investment and long-run trend dynamics.

In sum, our results suggest that cycle and trend are interconnected, which raises important questions as to both macroeconomic modelling and policy. Cycle-trend interaction requires a rethinking of the measurement of potential output and the output gap. Monetary policy which targets conventional output gap measures may thus rely on a biased signal of economic slack. More generally, our results support the view that alleviating the depth of recessions through monetary and fiscal policy appears to be of essence also for the long-run, i.e. trend path of aggregate output.

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A Appendix

A.1 Additional Tables and Graphs

Table 10: Firms by investment behaviour, weighted

	(1) All firms mean
Invest continuously with budget	0.058
Invest continuously w/o budget	0.198
Invest occasionally	0.237
Do not invest typically	0.507
Observations	5537

Notes: Data trimmed and weighted

Source: Forschungsdaten- und Servicezentrum (FDSZ) der Deutschen Bundesbank, BOP-F, Waves 6-8, own calculations.

Table 11: Change of Plans to invest, BOP-F

	(1) Planned RD only mean	(2) Planned TA only mean	(3) Planned RD and TA mean	(4) Didnt plan mean
No change, RD	0.737	0.986	0.681	0.993
No change, TA	0.984	0.799	0.749	0.992
No change, TA and RD	0.728	0.791	0.620	0.986
Increased, RD	0.079	0.014	0.061	0.007
Increased, TA	0.016	0.039	0.049	0.008
Decreased, RD	0.184	.	0.258	.
Decreased, TA	.	0.162	0.202	.
Observations	380	700	2164	1463

Notes: Trimmed data.

Source: Forschungsdaten- und Servicezentrum (FDSZ) der Deutschen Bundesbank, BOP-F, Waves 6-8, own calculations.

A.2 Questionnaire

Our empirical analysis is based on the following survey questions.

1. Planned to invest in 2020

   In the following section, we would like to ask you some questions on the topic of innovations. Innovations are new or improved products or business processes (or a combination thereof) that differ substantially from prior products or business processes and that the enterprise in question has introduced to the market or utilised itself. Innovations are often divided into research and development (R&D) and other innovations.

   QUESTION: Think back to the end of 2019, i.e. to the time before the COVID-19 pandemic. How much did you plan to spend on R&D activities and other innovation activities (excluding R&D)?

   Note: If you had no expenditure planned for one of the areas, please enter "0".

   Planned expenditure for R&D activities in 2020 amounted to: ....'000 euro,

   Planned expenditure for other innovation activities in 2020 amounted to: ....'000 euro

2. Actual investments

   QUESTION: How much did your enterprise actually spend on R&D activities , other innovation activities (excluding R&D?

   Note: If you had no expenditure in one of the areas, please enter "0".

   Actual expenditure for R&D activities in 2020 amounted to:....'000 euro

   Actual expenditure for other innovation activities in 2020 amounted to:....'000 euro

3. Reasons changed investments

   QUESTION: Which of the following changes linked to the coronavirus pandemic led to an adjustment of your plans regarding expenditure for R&D activities and other innovation activities (excluding R&D) in 2020?

   Note: Please select all answers that apply.

   0 = Category not selected 1 = Category selected

   1 = R&D activities 2 = Other innovation activities (excluding R&D)

   (a) Lower customer demand for existing products and services
   (b) Higher customer demand for existing products and services
   (c) Closures or work restrictions due to the coronavirus pandemic (hygiene rules, lockdown etc.)
   (d) Worse access to financing sources
   (e) Better access to financing sources
   (f) Worse access to intermediate inputs

(g) Better access to intermediate inputs

(h) Worse availability of suitable specialist staff

(i) Better availability of suitable specialist staff

(j) More uncertain economic outlook

(k) Other reasons linked to the coronavirus pandemic:

(l) No reasons linked to the coronavirus pandemic

4. Reasons no change in investments

   QUESTION: You stated that your enterprise did not adjust its plans regarding expenditure R&D or other innovation activities in 2020. Which of the following reasons were the most important?

   Note: Please select all answers that apply.

   0 = Category not selected 1 = Category selected

   (a) We would have reduced investment in innovation, but were not able to make adjustments.

   (b) We would have increased investment in innovation, but were not able to make adjustments.

   (c) Overall, the situation for my enterprise did not change significantly in 2020.

   (d) We had sufficient financial resources.

   (e) Other reasons

A.3 Full theoretical model

This section describes the full set of model equations outlined and discussed in section 5. The following sections explain in detail the remaining conditions of the model, in particular the underlying New Keynesian DSGE model features.

A.3.1 Final good production

The economy features two types of firms, intermediate goods producers and final goods producers which use intermediate goods as inputs. There is a continuum of measure unity of monopolistically competitive final goods producers. Final good firm i produces differentiated output Y_t^i. The final good composite is a CES aggregate of the respective differentiated final goods

$$Y_t = \left[\int_0^1 Y_t^{i\,\frac{\mu-1}{\mu}} di\right]^{\frac{\mu}{\mu-1}}. \tag{11}$$

The price level of final output is $P_t = \left[\int_0^1 P_t^{i\,1-\mu} di\right]^{\frac{1}{1-\mu}}$, where P_t^i is the price set by final good producer i. Output by final goods producer i's output is derived from cost minimization and equals to

$$Y_t^i = \left(\frac{P_t^i}{P_t}\right)^{-\mu} Y_t. \tag{12}$$

Prices are subject to Calvo price rigidities, where each final good firm can adjust its price with probability $1-\xi^p$. An indexation rule models the price adjustment by firms which cannot adjust their price

$$P_t^i = P_{t-1}^i \pi_{t-1}^{\iota_p} \bar{\pi}^{1-\iota_p}. \tag{13}$$

The price indexation parameter is denoted by ι_p, time t inflation by $\pi_t = \frac{P_t}{P_{t-1}}$ and steady state inflation by $\bar{\pi}$. Final good firms are subject to nominal marginal costs in the form of intermediate good input price P_t^m. The final good producer makes the choice about the optimal reset price P_t^* subject to final good demand (12) according to

$$\max_{P_t^*} \mathbb{E}_t \sum_{j=0}^{\infty} \xi_p^j \Lambda_{t,t+j} \left(\frac{P_t^* \prod_{k=1}^{j} \pi_{t+k-1}^{\iota_p} \bar{\pi}^{1-\iota_p}}{P_{t+j}} - \frac{P_{t+j}^m}{P_{t+j}}\right) Y_{t+j}^i. \tag{14}$$

A.3.2 Intermediate goods production

Total factor productivity growth occurs in the form of expanding varieties A_t of intermediate goods. Intermediate products A_t are produced by monopolistically competitive producers, where Y_t^{im} denotes output produced by intermediate good producer i. The composite of intermediate goods Y_t^m which is used as input by final good firms:

$$Y_t^m = \left[\int_0^{A_t} \left(Y_t^{im} \right)^{\frac{\vartheta-1}{\vartheta}} di \right]^{\frac{\vartheta}{\vartheta-1}}. \tag{15}$$

P_t^{im} denotes the nominal price set by producer i and the price of the intermediate good composite equals to $P_t^m = \left[\int_0^{A_t} \left(P_t^{im} \right)^{1-\vartheta} di \right]^{\frac{1}{1-\vartheta}}$. Intermediate good firms use labor and capital as inputs and produce by means of a Cobb-Douglas production technology:

$$Y_t^{im} = \theta_t \left(K_t^i \right)^{\alpha} \left(L_t^i \right)^{1-\alpha}, \tag{16}$$

where θ_t equals to a standard technology shock and thus the exogenous component of total factor productivity. W_t equals to the nominal wage and R_t^k to the rental rate of capital. The optimality conditions of intermediate goods producers' cost minimization are:

$$\alpha \frac{\vartheta - 1}{\vartheta} \frac{P_t^m}{P_t} \frac{Y_t^m}{K_t} = R_t^k \tag{17}$$

$$(1-\alpha) \frac{\vartheta - 1}{\vartheta} \frac{P_t^m}{P_t} \frac{Y_t^m}{L_t} = W_t. \tag{18}$$

$\frac{\vartheta}{\vartheta-1}$ describes the markup owed to imperfect competition in the intermediate goods sector and $\frac{P_t}{P_t^m}$ the the markup of the price of final relatively to the price of the intermediate good composite P_t^m respectively.

Intermediate good profits are a key are determinant of investment in R&D (5.1.3) as well as in technology adoption (section 5.1.4). Intermediate goods profits are equal for all firms ($\Pi_t^i = \Pi_t$) and derive as

$$\Pi_t = \frac{1}{\vartheta} \frac{P_t^m}{P_t} \frac{Y_t^m}{A_t}. \tag{19}$$

$K_t = \int_0^{A_t} K_t^i di$ and $L_t = \int_0^{A_t} L_t^i di$ are the conditions for market clearing in factor markets. From (16)-(18) follows aggregate intermediate good output[21] :

$$Y_t^m = \theta_t A_t^{\frac{1}{\vartheta-1}} K_t^{\alpha} L_t^{1-\alpha}. \tag{20}$$

A.3.3 Capital producers: investment

Capital producers transform final output to physical capital K_t which is sold to households at price Q_t, where capital is subject to adjustment costs f_i.[22] The representative capital producer

[21] To a first order $Y_t = Y_t^m$ holds.

[22] Note that the adjustment cost functions f_i, f_x and f_a are analogous but differ in the magnitude of adjustment costs (see section ??).

chooses the $\{I_{t+j}\}_{j=0}^{\infty}$ in order to maximize expected discounted profits

$$\mathbb{E}_t \left\{ \sum_{j=0}^{\infty} \Lambda_{t,t+j} \left[Q_{t+j} I_{t+j} - \left(1 + f_i \left(\frac{I_{t+j}}{I_{t+j-1}} \right) \right) I_{t+j} \right] \right\}. \tag{21}$$

From profit maximization obtains that the marginal costs of the generation of investment goods is equal to the respective price:

$$Q_t = 1 + f_i \left(\frac{I_t}{I_{t-1}} \right) + \frac{I_t}{I_{t-1}} f_i' \left(\frac{I_t}{I_{t-1}} \right) - \mathbb{E}_t \left[\Lambda_{t+1} \left(\frac{I_t}{I_{t-1}} \right)^2 f_i' \left(\frac{I_t}{I_{t-1}} \right) \right]. \tag{22}$$

Lastly, the law of motion for capital equals to

$$K_{t+1} = (1 - \delta) K_t + I_t. \tag{23}$$

A.3.4 Employment agencies

A continuum of households monopolistically supply specialized labor L_t^i. As in Erceg et al. (2000), a large number of competitive employment agencies transform specialized labor to a homogeneous input L_t. L_t is used in intermediate goods production and equals to

$$L_t = \left[\int_0^1 L_t^{i\,\frac{\omega-1}{\omega}} di \right]^{\frac{\omega}{\omega-1}}. \tag{24}$$

The cost minimization of employment agencies delivers the labor demand for type i:

$$L_t^i = \left(\frac{W_t^i}{W_t} \right)^{-\omega} L_t, \tag{25}$$

where the nominal wage of i equals to W_t^i. The aggregate wage at which the labor composite is bought by intermediate goods firms equals to

$$W_t = \left[\int_0^1 W_t^{i\,1-\omega} di \right]^{\frac{1}{1-\omega}}. \tag{26}$$

A.3.5 Households

The household problem can be characterized as follows. Household i maximizes utility

$$\mathbb{E}_t \left\{ \sum_{j=0}^{\infty} \beta^j \left[log \left(C_{t+j} - h C_{t+j-1} \right) - \frac{\psi}{1+\nu} L_{i,t+j}^{1+\nu} \right] \right\} \tag{27}$$

respect to the budget constraint

$$\frac{W_t^i}{P_t} L_t^i + R_t \frac{B_t}{P_t} + \left(R_t^k + (1 - \delta) Q_t \right) K_t + \Pi_t = C_t + \frac{B_{t+1}}{P_t} + Q_t K_{t+1}, \tag{28}$$

where C_t equals consumption and h habit persistence $(0 < h < 1)$.[23] B_t states nominal riskless bonds. A fraction $1 - \xi_w$ of households can adjust their wage in period t. The optimal wage follows from

$$\max_{W_t^*} \mathbb{E}_t \sum_{j=0}^{\infty} \left\{ (\xi_w \beta)^j \left[\frac{U_{c,t+j}}{P_{t+j}} L_{t+j}^i W_t^* \prod_{k=1}^{j} (1+g)\, \pi_{t+k-1}^{\iota_w} \bar{\pi}^{1-\iota_w} - \frac{\psi}{1+\nu} \left(L_t^i\right)^{1+\nu} \right] \right\} \tag{29}$$

subject to labor demand (25). Households which cannot reset wages set their wage via the indexation rule

$$W_t^i = W_{t-1}^i (1+g)\, \pi_{t-1}^{\iota_w} \bar{\pi}^{1-\iota_w}. \tag{30}$$

A.3.6 Monetary policy

The central bank sets nominal interest rates by means of policy rules, where a standard inertial Taylor rule constitutes the benchmark case:

$$R_t = (R_{t-1})^{\rho_r} \left(\left(\frac{\pi_t}{\pi^*}\right)^{\gamma_\pi} \left(\frac{y_t}{y_t^{pot}}\right)^{\gamma_y} R_n \right)^{1-\rho_r} r_t^m, \tag{31}$$

where R_t denotes the nominal interest rate, γ_π and γ_y the weights on inflation and the output gap respectively, ρ_r the Taylor rule persistence parameter and R^n the steady state nominal interest rate.[24] The monetary policy shock r_t^m follows an AR(1) process $(log\,(r_t^m) = \rho^m log\,(r_{t-1}^m) + \epsilon_t^m)$. The policy rule entails a standard output gap measure in line with standard New Keynesian DSGE models, where y_t and y_t^{pot} refer to detrended output and potential output respectively.[25] The central bank may be constrained by the zero lower bound (ZLB) on nominal interest rates.[26]

$$R_t \geq 1. \tag{32}$$

A.3.7 Aggregation

The economy is subject to the aggregate resource constraint

$$Y_t = C_t + \left[1 + f_i\left(\frac{I_t}{I_{t-1}}\right)\right] I_t + \left[1 + f_a\left(\frac{I_t^a}{I_{t-1}^a}\right)\right] I_t^a + \left[1 + f_x\left(\frac{X_t}{X_{t-1}}\right)\right] X_t + G_t, \tag{33}$$

[23]The model features a shock to liquidity demand in the form of an AR(1) process which lowers safe asset holdings at the expense of consumption, thus distorting the Euler equation. The full set of equations is listed in the Online Appendix.

[24]Target inflation π^* is set to 2% annually. Steady state annualized nominal interest rates equal to 3% annually, matching a long-run real interest rate of 1%, in line with **?** (see **??** for more details on the model calibration).

[25]More precisely, potential refers to the allocation under flexible prices and wages and detrended output is defined as $y_t = \frac{Y_t}{A_t}$.

[26]The occasionally binding constraint is implemented by means of the piecewise-linear method Occbin (**?**).

which states that final output is consumed, used for physical capital investment, government spending, as well as for expenditure on technology adoption and innovation.[27].

[27] This section presented the central equilbirium conditions. The remaining conditions characterizing the equilibrium and model calibration are listed in the online appendix. For a more detailed model representation see also Elfsbacka Schmöller (2022)