Short-run shocks, longer-run consequences: How business cycle fluctuations affect technological progress

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[1]joint work with Sascha A. Keweloh, a slightly different version appeared as Keweloh, S.A. and Andre Seepe (2020), *Monetary policy and the stock market - A partly-recursive SVAR estimator*, SFB 823 Discussion Paper series No. 32/2020, http://dx.doi.org/10.17877/DE290R-21722

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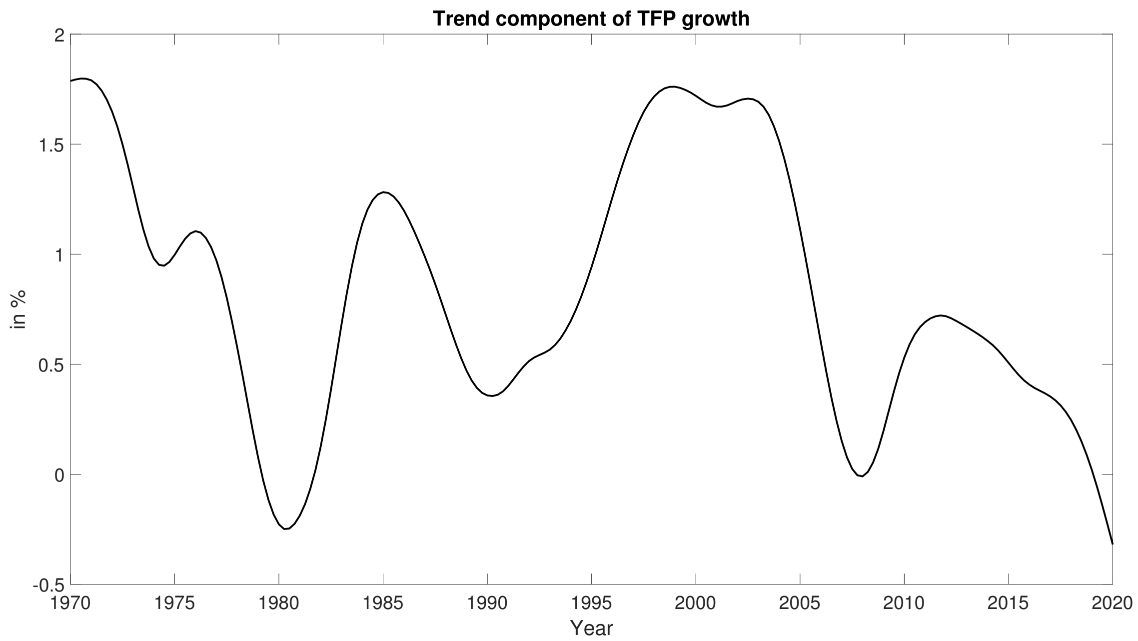
1 Introduction

Traditional textbook macroeconomics typically discusses short-run business cycle fluctuations and long-run growth apart from each other, which is called the classical dichotomy between the short and long run. Lucas (1987) argued that in a, at this time standard, calibrated macroeconomic model, the benefits of evening out business cycle fluctuations are negligible compared to the ones from fostering long-run growth, which led to the proposition that macroeconomists should shift their attention to long-run growth rather than the business cycle. On the other side, the opposing view that short and long run are not dichotomous but integrated, dates back to the seminal work of Schumpeter (1942), who argued that through creative destruction the business cycle is a logical consequence of economic growth. After Lucas's influential paper, many authors went back to the idea of integration between business cycles and long-run growth, arguing in favor of a more holistic view on both.

For instance Caballero et al. (1994), Aghion and Saint-Paul (1998) and Barlevy (2007) discuss the idea of the "cleansing effect of recessions". Aggregate TFP is the average of the productivity of all individual firms and new, better ideas arrive every period. During a recession, firms with low productivity are more likely to go bankrupt and leave the market than firms with higher productivity, thus average productivity increases. Consequently, any event that leads to a cyclical downturn should stir up aggregate productivity. However, Fatas (2000) points out that in the data economic growth as well as R&D is procyclical. He sees the main reason for this in the research decision depending on firm profitability. Research is an investment into future productivity, so firms that perceive a higher return to this investment will research more and experience higher productivity growth. In consequence, a positive demand shock leads to higher firm profitability and thus more research and faster technological progress, while recessions are slowing down the growth process. In contrast to that, Francois and Lloyd-Ellis (2003) argue that the integration of business cycles and long-run growth is due to animal spirits of the economic agents. They show that in their model there exist two equilibria, one is acyclical and fits the classical dichotomy, while the other is cyclical and the business cycle is an integral part of economic growth like in Schumpeter (1942). Ideas are produced by using a part of labor for the research process. In the cyclical equilibrium, a boom induces increasing labor costs and thus higher innovation costs. Consequently, firms will lower their innovation effort, productivity growth is lower and the expected future production decreases, which leads to a decline in the interest rate. The decline in the interest rate then leads to lower demand in the next period, thus lower labor and innovation costs and higher productivity growth. The up and down of the business cycle in this case is an integral part of technological progress. Barlevy (2004) suggests an AK-model with diminishing returns to capital investment, which leads to economic growth being a concave function of investment by construction. In this case every business cycle shock that reduces investment directly reduces economic growth. The aforementioned papers resemble the first attempts to systematically integrate the business cycle and economic growth through various mechanisms, may it be a cleansing effect of recessions, fluctuations in profitability, animal spirits or the assumption of specific properties for the production process.

The nowadays mainstream framework for the integration of short-run business cycles and longer-run technological progress hails back to the seminal paper of Comin and Gertler (2006). They observe that traditional filter techniques, like the HP or bandpass filter, tend to sweep the bulk of medium-run fluctuations into the trend component. For example, figure 1.1 shows the trend component of U.S. TFP growth between 1970 and 2020 as provided by Fernald (2012-2019). As it becomes evident,

Figure 1.1: Trend component of HP-filtered TFP growth provided by Fernald (2012-2019) (smoothing parameter set to $\lambda = 1600$)



trend growth is not nearly constant as implied by standard macroeconomic models, but underlies medium-term fluctuations, where the swings in the growth rate can last over 10 years. Comin and Gertler (2006) argue that in an endogenous growth model, short-run shocks can have longer-run implications through the nexus of technology adoption. Typical business cycle shocks affect R&D instantaneously, but the new ideas have to gradually diffuse through the economy before the full effect of the change in research embodies within TFP. Comin (2009) provides further evidence that short- and medium-run fluctuations originate from the same shocks, which are of low persistence themselves. In particular, they find that the same variables that are associated with high frequency fluctuations (for instance output, consumption or investment) also have a medium-run component and vice versa. Concerning macroeconomic models, the technology adoption mechanism allows to generate these medium-run fluctuations with short-run shocks. Moreover, Kogan et al. (2017) construct an innovation measure that tries to capture the private rather than scientific value of innovations by observing stock market responses to patents. With their new measure, they find that technological innovations alone can induce significant medium-run fluctuations in output and productivity. They also find evidence in favor of the Schumpeterian view of technological progress, in particular that new ideas lead to an increase in economic growth, sectoral reallocation and the marginalization of older technologies.

The recent related literature has added the technology adoption mechanism in otherwise standard models and analyzed the longer-run implications of traditional macroeconomic shocks. For instance Bilbiie et al. (2012) study firm entry over the business cycle and introduce technology adoption in form of a time-to-build lag for entrants to the market. Innovations open up the opportunity to found a new firm, which however is not able to produce immediately with the new technology, but only after a predefined period of setting up the firm. Thus, technology shocks that cause economic expansions induce firm entry, which however does not respond immediately, but over time. Benigno and Fornaro (2017) study the impact of the Zero Lower Bound encountered during the Great Recession in a Keynesian model featuring endogenous growth and technology adoption. In their paper, technology adoption is not included via a predefined time-to-build lag, but more like in Comin and Gertler (2006) by a continuous diffusion process. They find that the missing monetary policy reaction to demand fluctuations during a Zero Lower Bound period makes animal spirits and multiple steady states possible. If households expect an economic downturn and reduce their demand for goods, firms have lower liquidity and liquidity constrained R&D decreases. By technology adoption, the reduction in R&D leads to medium-term lower productivity and an economic downturn, thus the household expectations are self-fulfilling. During normal times, the central bank can counteract demand declines, thus there is one stable growth path. In consequence, Benigno and Fornaro (2017) see the Zero Lower Bound as a major reason for the productivity growth slowdown during the Great Recession, as pessimistic expectations decreased the willingness to invest in research. Anzoategui et al. (2019) in a similar model find that the downturn in demand also caused a slowdown in the technology adoption rate, thus the medium-run effect of research on productivity turned out to be lower during the Great Recession. They reason that a positive liquidity demand shock during the Great Recession forced the households to decrease savings and, consequently, there was less investment in physical capital and productivity enhancements in the form of research and adoption spending. They find that the liquidity demand shock explains the bulk of the observed productivity growth slowdown during the financial crisis.

The present dissertation stands in the tradition of this technology adoption related literature, as it takes a look on further standard macroeconomic shocks and their longer-run consequences, in particular matching efficiency, inflation target, monetary policy, news and noise shocks. It adds to the existing literature by studying standard macroeconomic models that typically exclude endogenous growth by including it and providing empirical support for the results regarding the longer-run effect of these shocks.

Chapter 2 studies the impact of matching efficiency shocks on the labor market and subsequent technological progress. For the U.S., the slowdown in productivity growth during the Great Recession was accompanied by an outward shift in the Beveridge Curve (see Hobijn and Şahin (2013), Sedláček (2014) or Diamond and Şahin (2015)). The question stands, if these two events are related and in which direction the causality goes. Even long before the event of the Great Recession, there was work on how the labor market might influence technological progress. For instance Bean and Pissarides (1993) argued that unemployment leads to less income and thus less means to invest for households, which in an AK-model directly leads to lower economic growth. Mortensen (2005) brought up the idea that the tightness of the labor market (so the relation of vacancies to unemployed) plays a major role for the entry decision of outside firms. If there are less unemployed per vacancy, firms have a lower probability of finding a worker and hiring costs increase, consequently firms might decide to postpone or cancel firm entry. If new firms are the ones bringing new ideas into the economy like in standard horizontal growth models, technological progress declines. However, Mortensen (2005) discusses only the effect of the labor market tightness and not overall matching efficiency on technological progress. Wheeler (2007) and the recent paper of Martellini and Menzio (2020) include this discussion about the role of matching efficiency in models of economic growth in their work. They assume that worker skills are increasing over time and are distributed among the population, where firms have specific needs regarding the worker skill for each firm. A lower matching efficiency reduces the probability of finding workers that have a fitting skill set and the resulting skill mismatch leads to lower productivity of the respective firms. Wheeler (2007) and Martellini and Menzio (2020), however, allow increasing productivity only by an exogenous increase in worker skills and not by technological advancement of the firms.

Chapter 2 of the present dissertation brings together the work of Mortensen (2005), Wheeler (2007) and Martellini and Menzio (2020) with a model containing endogenous technological progress through technology adoption. It is assumed that intermediate firms are in Schumpeterian competition for the spot as incumbent in the market, but are subject to standard labor market frictions, where vacant jobs are filled according to a matching function. Thus, the lower the matching probability the higher the hiring costs per worker for the firms. Potential entrants, who compete with the incumbents for the spot in the market, do not have a worker stock, so the hiring costs impose an entry barrier to them. As by Schumpeterian competition only the firm with the highest productivity can stay in the market, a potential entrant would have to spend more on research than the incumbent in order to replace it. Without any further restrictions, both incumbent and potential entrant would choose to set research spending equal to the expected value of being next period's incumbent, where both are indifferent regarding their innovation choice. However, the introduction of the additional entry cost due to hiring costs drives a wedge between the continuation value of incumbents and the entry value of potential entrants, which allows the incumbents to lower their innovation effort in order to make positive intertemporal profits. Thus, the lower the competitive pressure from the potential entrants, the lower the innovation effort and longer-run technological progress in the whole economy. Estimating the model using Bayesian techniques reveals that the outward shift in the Beveridge Curve during the Great Recession was induced by a significant drop in matching efficiency over about 20% (see Sedláček (2014) for econometric proof). While matching efficiency shocks are not a big contributor to endogenous technological progress during normal times, the drop during the Great Recession was a major force behind the slowdown in endogenous productivity growth during the Great Recession, even ahead of demand or TFP shocks that the related literature identifies as the main drivers, and led to a permanent 0.6% loss in TFP. Thus, to answer the causality question: The bad conditions on the labor market were a major cause of the slower endogenous technological progress.

The third chapter discusses a discrepancy in the literature concerning the link between inflation and longer-run economic growth. On the one hand, there is a vast amount of papers finding a negative relationship between an increase in the inflation rate and subsequent economic growth within and across countries (see Bruno and Easterly (1996), Bruno and Easterly (1998), Vaona and Schiavo (2007), Omay and Kan (2010), Bick (2010) or Kremer et al. (2013)). On the other hand, recent papers like Moran and Queralto (2018) or Bianchi et al. (2019), studying technological progress under technology adoption after a monetary policy shock, find that expansionary monetary policy, which induces inflation, is beneficial for productivity growth. During the Great Recession, central banks faced the Zero Lower Bound and in order to prevent the repeat of this event, some authors like for example Blanchard et al. (2010) suggested to permanently increase the inflation target and thus the monetary policy rate and long-run average inflation, which would give central banks more space before hitting the Zero Lower Bound. How does this permanent or at least longer-run shock to monetary policy and inflation affect technological progress? Would the longer-term higher monetary policy rate and the higher inflation decrease technological progress and if so how can a traditional short-run positive monetary policy shock be detrimental for technological progress, as found in Moran and Queralto (2018) or Bianchi et al. (2019)?

In chapter 3, a Newkeynesian model with endogenous technological progress under technology adoption is proposed to answer these questions. Again, firms are in Schumpeterian competition for the spot as incumbent in the market. Thus, in order to not be destroyed by a competitor, they have to invest the expected discounted value of continuing the firm into technological progress. Firms are subject to quadratic price adjustment costs, which in the standard model implies that inflation leads to a markup decrease. The key difference between a classical monetary policy and an inflation target shock is that the interest rate change due to a monetary policy shock is much less persistent, as for instance in Smets and Wouters (2003) or Ireland (2007). The reasoning is that if the central bank deviates from its monetary policy rule for a longer time, this cannot be just craziness but has to be a change in its policy target. In fact, it is assumed that the monetary policy shock has a lower persistence than the duration necessary for a new technology to be adopted. Expansionary monetary policy then leads to a lower discounting of the firm continuation value, but by being of a shorter duration than the technology adoption process, inflation returns back to its long-run mean fast and the future markup that is relevant for the innovation decision is insignificantly affected by the monetary policy shock. In consequence, the discounting effect outweighs the markup effect, firms spend more on research and technological progress accelerates. However, a positive inflation target shock, the more persistent variant of a monetary policy shock, affects longer-run inflation and the future markup relevant for the innovation decision decreases stronger than under the monetary policy shock. Estimating the model using Bayesian methods, it turns out that in this case the markup effect dominates the discounting effect, firms spend less on research and technological progress is slowed down. The point estimate hints that TFP is permanently about 0.05% lower, if the policy rate and long-run inflation are permanently increased about 5 percentage points, which would have been necessary to avoid an encounter with the Zero Lower Bound during the Great Recession (see Blanchard et al. (2010)). The model is thus able to both explain a longer-run negative effect of inflation on technological progress and a short-run positive effect of expansionary monetary policy. Furthermore, this part of the dissertation cautions against the increase of the monetary policy rate to avoid the Zero Lower Bound, as it is costly in terms of longer-run productivity.

Chapter 4, a joint work with Sascha A. Keweloh, deals with an issue related to the matter of the third chapter. We argue that introducing stock returns and the monetary policy rate at the same time into an SVAR leads to an identification problem that cannot be solved by standard short- or long-run restrictions. One would assume that at the, for macroeconomic data usual, quarterly data frequency, both the stock market and monetary policy can react immediately to a shock hitting the respective other agent, which makes short-run zero restrictions not suitable for identification. Furthermore, there is no conclusive evidence in the literature that gives reasons to set the impact effect of monetary policy or stock market shocks on stock prices or the nominal interest rate to another specific number, so short-run restrictions seem to be out of the question for the matter at hand. Thus, Bjørnland and Leitemo (2009) or Kontonikas and Zekaite (2018) impose a long-run zero restriction on the effect of monetary policy shocks on stock prices, which is reasoned by the long-run monetary neutrality featured by standard macroeconomic models. However, in light of the recent findings of Moran and Queralto (2018) or Bianchi et al. (2019) that monetary policy shocks have a significant longer-run effect on aggregate productivity, imposing a zero long-run effect of monetary policy on stock prices appears to be too restrictive and possibly wrong.

In order to avoid imposing too much structure from the theory, we propose a new partly-recursive, partly data-driven SVAR estimator. We show in a modeling exercise that, depending on the model, a monetary policy shock can have a long-run negative or no long-run effect on stock prices. Imposing a long-run restriction thus boils down to choosing a model ex ante, while our approach allows to test the model implications without imposing them. We assume that a first block of variables containing standard controls like output, investment and inflation can be identified by a standard recursive ordering, while a second block containing stock returns and the nominal interest rate is completely unrestricted. The assumption of a recursive block is not necessary for identification, but improves the precision of the estimates and thus allows for narrower confidence bands that enable us to draw more conclusive results from the estimation. Furthermore, introducing a recursive block makes it easier for the econometrician to label the resulting structural shocks, as the shocks of the non-recursive block are only identified up to labeling (see for instance Keweloh (2019)), and makes identification possible even if more than one structural shock is Gaussian, but all than at most one of the Gaussian structural shocks can be moved to the recursive block. The non-recursive block is estimated by GMM using moments beyond the variance, which requires $n-1$ of the n shocks identified this way to be non-Gaussian. We provide evidence that this requirement is fulfilled in an SVAR containing stock returns and the nominal interest rate in the non-recursive block. In line with the related literature and the previous chapter of this dissertation, we find no supportive evidence for the long-run neutrality of monetary policy, as an exogenous increase in the federal funds rate leads to permanently lower stock prices, investment and output, which however is associated with high uncertainty. A stock market shock on the other hand leads to an increase in output, investment and the federal funds rate, but the effect vanishes after a few quarters.

The fifth chapter then uses the method layed out in the previous chapter to simultaneously identify news and noise shocks. Since the seminal paper of Beaudry and Portier (2006), the inclusion of stock prices in SVARs is used to examine news shocks. A news shock is here defined as a shock that is not correlated with current TFP, but strongly with future TFP. Additionally, Lorenzoni (2009), Blanchard et al. (2013) or L'Huillier and Yoo (2017) discuss so called noise shocks, which are defined as shocks that never have a direct endogenous effect on TFP and only work through expectations. For that matter, the related literature usually assumes a signal extraction problem, so economic agents do not directly observe news, but only a signal that includes true news and noise. For example Blanchard et al. (2013) argue that news and noise shocks in that case cannot be identified using standard

SVAR methods, as only one independent signal is not enough to extract two structural shocks. However, stock prices are only one variable that contains information concerning news about the future. So what is needed is another variable that contains additional information about news and noise. Comin et al. (2009) and Kung and Schmid (2015) bring up the idea to interpret research related shocks as news shocks, as through necessary technology adoption beforehand they are unrelated to current TFP, but affect longer-run technological progress and are thus correlated with future TFP. In this sense, research spending is an additional variable besides stock prices that contains information about news and noise.

In the fifth chapter it is argued that including both, stock prices and research spending, in an SVAR allows to simultaneously identify news and noise shocks. To solve the singularity hailing from the signal extraction problem, it is assumed that researchers have an informational advantage concerning the truth of news compared to the other economic agents, as they are closer to the source of research related news. This allows for a testable implication, namely that for a noise shock that induces the same stock price boom as a news shock, the research spending response should be more cautious. Furthermore, as a noise shock has no direct effect on productivity, the productivity and stock price responses should be considerably weaker for the noise shock compared to the news shock. In order to be able to not impose this structure on the data when testing the theory, but be as agnostic as possible, the identification scheme based on moments beyond the variance as in the previous chapter is employed for news and noise shocks. It turns out that this approach is able to identify a news shock that has similar features as for instance in Beaudry and Portier (2006) and a noise shock that confirms the testable implications from the theory, namely a compared to news shocks more cautious response in research spending and a weaker response of stock prices and TFP. Thus, the empirical evidence is in favor of the assumption that research spending to some extend provides information about the truth of news.

The sixth chapter concludes and summarizes the contribution of the present dissertation to the existing literature. Mainly this dissertation continues to examine the longer-run implications of business cycle shocks standard in the macroeconomic literature that were not considered yet within a model framework containing endogenous productivity under technology adoption. It finds that matching efficiency shocks reduce technological progress and were a major contributor to the slowdown in endogenous productivity growth during the Great Recession. Furthermore, inflation target shocks that induce an increase in longer-run inflation also have a negative effect on technological progress and thus are a, in terms of productivity, costly way to hedge against the Zero Lower Bound. Concerning monetary policy shocks, the recent result of them having longer-run implications is confirmed using a new SVAR estimator, in particular a contractive monetary policy shock leads to a longer-run decrease in real stock prices, output and investment. At last it is shown, how news and noise shocks can simultaneously be identified by using research spending as a further variable in an SVAR. It turns out that noise shocks induce a more cautious response in research spending than news shocks and have a weaker effect on productivity and stock prices.

2 Outward shifts in the Beveridge Curve, losses in TFP: How search and matching influences technological progress

2.1 Introduction

Between the years 2008 and 2010 a persistent outward shift in the U.S. Beveridge Curve has been observed[1], which is largely attributed to a significant drop in overall matching efficiency between firm vacancies and unemployed[2]. At the same time, a notable productivity growth slowdown took place in the U.S.[3], resulting in persistently lower aggregate productivity. The present paper argues that these two observations are causally linked, more specifically that the outward shift in the Beveridge Curve during the Great Recession is a major contributor to the subsequently lower productivity growth.

The general idea is as follows: Decreasing matching efficiency, which leads to an outward shift of the Beveridge Curve, reduces the probability of filling a vacancy for firms and as maintaining a job posting is assumed to be costly, it becomes more expensive for them to hire a given number of workers. There are two types of firms: Incumbents, who are in the market, have a worker stock for production and sell their products, and outside firms, who have no worker stock and are not producing, but compete with incumbents for their position in the market. Both are in Schumpeterian competition for the spot as future incumbent, thus it is assumed that the future incumbent will always be the firm with the highest technology level. Outside firms are constantly trying to replace the current incumbents by attaining a higher productivity level, for which they have to invest in new technologies. Without any further restrictions, otherwise free entry to the competition for the spot in the market dictates that outsiders and incumbents would be willing to spend the expected discounted value of being the incumbent in the next period for innovation. Spending less means to lose the Schumpeterian competition, spending more yields a negative value of being the incumbent. Consequently, at this indifference point, the intertemporal profit for the incumbent is zero. However, here outside firms do not have any worker stock and thus incur additional hiring costs if they wish to overtake the position as incumbent, so they have a structural disadvantage

[1] see Diamond and Şahin (2015), Hobijn and Şahin (2013), Barlevy (2011) or Sedláček (2014)
[2] see Sedláček (2014) or Furlanetto and Groshenny (2016)
[3] see Sprague (2017)

compared to the current incumbent firms, who already have a worker stock. So hiring costs impose an additional entry cost to outside firms, which is higher if the matching probability is lower. Higher entry costs, however, lower the value of becoming the incumbent for outside firms and thus reduce the amount they are willing to spend for innovation, which reduces the competitive pressure in the race for the highest productivity on the incumbent firms they are competing with and allows them to reduce spending on innovations as well, in order to incur positive intertemporal profits. Consequently, innovation in the economy and therefore endogenous TFP growth decreases, if the matching efficiency between firm vacancies and unemployed decreases.

Estimating the model using Bayesian techniques and U.S. data between 2000 and 2019, it turns out that during normal times matching efficiency shocks are not responsible for fluctuations in the TFP growth rate to a large extent, but for the Great Recession period between 2008 and 2012 this changed and the observed significant exogenous decrease in aggregate matching efficiency about over 20% was a major contributor to the decrease in endogenous TFP growth during this time. It turns out that the total loss in TFP caused by the strong decline in matching efficiency during the Great Recession is permanent and summed up to an over 0.6% lower TFP in the beginning of 2019.

How does the present paper fit into the related literature about the interrelation of TFP and the Beveridge Curve? There are lots of papers discussing how changes in the labor market might affect productivity: For instance Bean and Pissarides (1993) argue that in a model with constant returns to capital, unemployment leads to lower economic growth, as being unemployed leads to lower income and thus lower means to invest into capital. However, as it can be seen in the data, the growth in trend TFP was also low after the Great Recession, when the unemployment rate recovered to a long-term low, but the Beveridge Curve was still shifted outwards. Mortensen (2005) proposes a model, where firms are in competition for workers such that finding a worker easier makes it more attractive for entrants to enter the market with new technologies, which is quite close to the model proposed here. However, Mortensen (2005) only considers the effect of labor market tightness, so the ratio of vacancies to unemployed, on the entry decision, where a higher number of contacts between firms and unemployed raises the attractiveness of market entry. But again, there are plenty of movements and thus changes in the labor market tightness along the Beveridge Curve in the data after it shifted out, while trend TFP growth remained low, so it seems that ultimately the matching probability is much more decisive than the labor market tightness it is attributed to. The present paper, however, stays agnostic and allows also shocks to the labor market tightness in the form of job destruction shocks in order to assess their importance relative to matching efficiency shocks. Indeed it turns out that they have a rather negligible influence on endogenous technological progress compared to matching efficiency shocks. Consequently and in line with this paper's findings, shifts of the entire Beveridge Curve have to affect trend TFP more than fluctuations in the labor market tightness. Wheeler (2007) and Martellini and Menzio (2020) discuss the relationship between matching efficiency and productivity as in the present paper. They impose a distribution of worker skills, where a higher matching efficiency increases the match quality between the skill requirements of firms and the skill level of workers such that overall productivity increases. The present paper abstracts from labor productivity given by an exogenous skill distribution of workers and models an endogenous innovation sector, which allows to study the effect of matching efficiency shocks on endogenous technological progress. Furthermore, it applies its findings to the decline in trend TFP growth observed after the Great Recession.

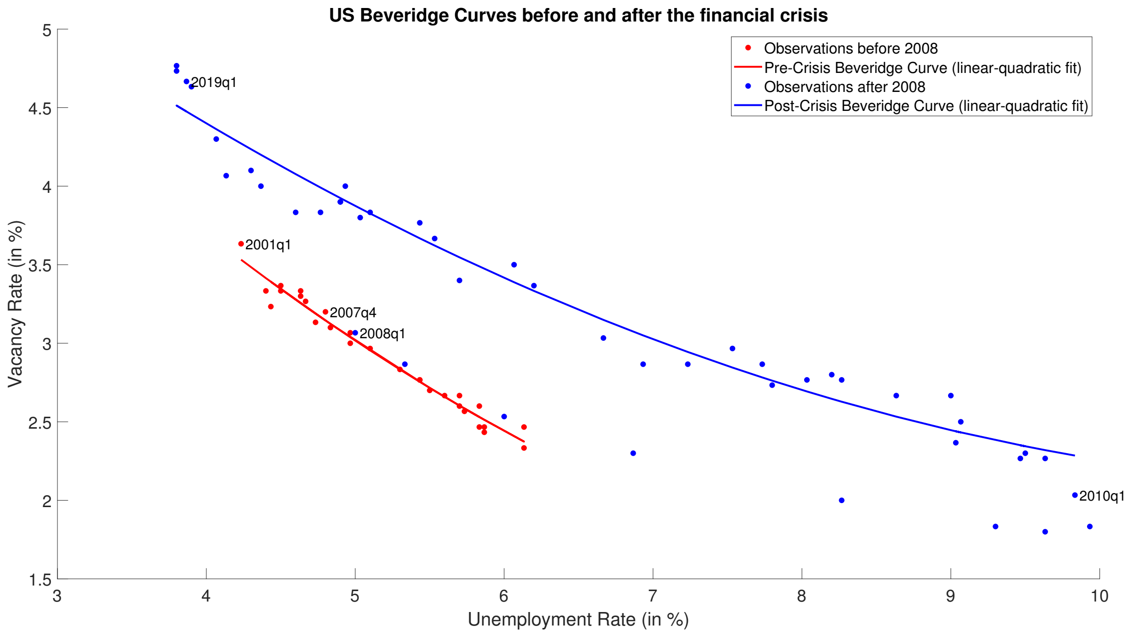
On the other side, there are many papers discussing the reverse effect of TFP shocks on labor market variables, mainly discussing the reaction of job creation and destruction to productivity shocks. Aghion and Howitt (1994) argue that there is a capitalization effect (higher productivity increases the return from new jobs and thus job creation) and a creative destruction effect (higher productivity makes some jobs obsolete and increases job destruction). Pissarides and Vallanti (2007) and Kaas and Kircher (2015) find that in practice TFP growth has a negative effect on unemployment and that faster growing firms require more workers than slower growing ones, which means that the capitalization effect should be stronger than the creative destruction effect. Michelacci and Lopez-Salido (2007) argue that the type of technological change is important, where neutral change leads to more job destruction and investment specific change leads to less job destruction. Finally, Zagler (2009) proposes a model, where structural change is the driving factor behind productivity growth, but also leads to sectoral reallocation of labor and thus unemployment during the reallocation process. So when discussing the effects of changes in the search and matching process on TFP growth, the reverse effect has to be taken into account, which is done in the present paper's model by allowing TFP shocks to affect the hiring decision of the firms. Still it turns out that matching efficiency shocks are the most important driver of the slowdown in endogenous TFP growth after 2010.

The remainder of this paper is organized as follows: Section 2 gives a short insight into the behavior of the Beveridge Curve and TFP between 2000 and 2019, laying out the case for this paper. Section 3 presents the model and shows how matching efficiency affects endogenous TFP growth. In Section 4 the model is estimated and a shock decomposition is performed, to demonstrate to what extent matching efficiency shocks and especially the strong decline in matching efficiency during the Great Recession between 2008 and 2012 affected endogenous technological progress. Section 5 concludes.

2.2 A first look at the data

Before diving into theory, a first look at the data is intended to reveal the crucial observations that are to be explained afterwards. Figure 2.1 shows a scatterplot of the U.S. vacancy rate against the U.S. unemployment rate. Red circles depict observations before the first quarter of 2008 (so before the Great Recession) and blue ones observations afterwards. Furthermore, it shows a linear quadratic fit from an OLS regression of the vacancy rate on a constant, the unemployment rate and the squared unemployment rate before 2008 (red line) and after 2010 (blue line), which is intended to visualize the Beveridge Curve. The linear-quadratic approximation of the Beveridge Curve is solely for visualization purposes and not to impose any theoretical structure on it. Data for the quarterly vacancy rate is taken from the Job Openings and Labor Turnover Survey (JOLTS) data set (U.S. Bureau of Labor Statistics (2020b)), which tries to extrapolate the hard to measure true total vacancies by observing for instance online and offline job offers, help wanted signs and firm surveys. Though it might still not be able to catch every vacancy, especially only internal employment adverts, many related papers (for example the JOLTS dataset is used in Hobijn and Şahin (2013), Sedláček (2014) or Diamond and Şahin (2015)) consider it the best approximation available. Data for the quarterly unemployment rate is from the Current Population Survey (CPS) of the U.S. Bureau of Labor Statistics (2020a). As it can be seen, between the first quarter of 2008 and the first quarter of 2010 the U.S. Beveridge Curve shifted outwards, which in the literature is largely attributed to a drop in overall matching efficiency between vacancies and unemployed after the Great Recession (e.g. Furlanetto and Groshenny (2016)). For instance Sedláček (2014) and Barlevy (2011) estimate the drop in matching efficiency to be around 15-20% after the Great Recession. Diamond and Şahin (2015) argue that outward shifts in the Beveridge Curve regularly accompany recessions and the outward shift during the Great Recession can be ex-

Figure 2.1: U.S. Beveridge Curves before and after the financial crisis of 2008. Beveridge Curves are visualized as the fitted values of an OLS regression of the vacancy rate on the unemployment rate and the squared unemployment rate. The pre-crisis period is defined as $t < 2008$, while the post-crisis period is defined as $t \geq 2010$.

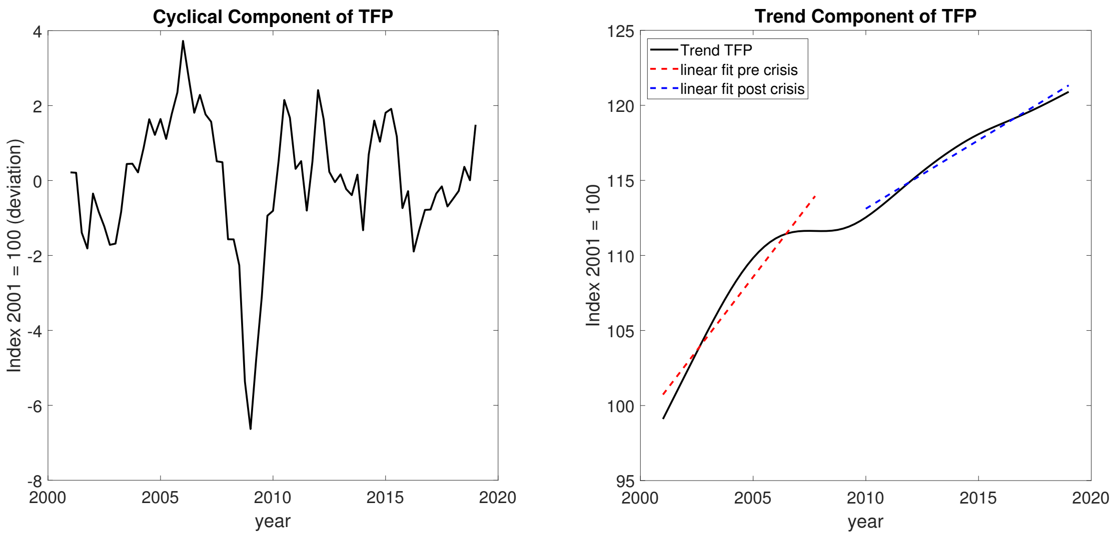


plained by workers having to relocate from high labor turnover industries like the housing and construction sector (where the crisis originated) to low turnover ones like health care[4]. This paper follows Furlanetto and Groshenny (2016) in interpreting aggregate matching efficiency shocks as "take all shocks" for any structural mismatches on the labor market not captured by the set of other shocks included in the model or as a "Solow residual" of the matching function. This paper is not concerned about the exact microeconomic origins of the fluctuations in aggregate matching efficiency, as they are irrelevant to the proposed model mechanism, as long as they behave like an exogenous aggregate matching efficiency shock.

What also can be observed is that TFP growth slowed down after the Great Recession. Figure 2.2 depicts the cyclical and trend component of TFP received by HP-filtering the quarterly TFP series provided by Fernald (2012-2019) (smoothing parameter set to a common value of $\lambda = 1600$). The huge negative TFP shock that is associated with the Great Recession in 2008 is visible in the cyclical component. What is striking is that between 2008 and 2010 the long-run trend component of TFP was almost horizontal with approximately zero growth and after 2010 the

[4]for further evidence see Hobijn and Şahin (2013)

Figure 2.2: Decomposing TFP (source Fernald (2012-2019)) into a cyclical and trend component using the two-sided HP-filter with smoothing parameter $\lambda = 1600$. Linear fit of trend TFP is given by an OLS regression of trend TFP on a linear time trend, pre- and post-crisis periods defined as above.



long-run TFP path lies persistently below the path before 2008 without any sign of recovery, which can be seen by comparing the red and blue line (linear fits of the growth paths of TFP before and after the Great Recession) in figure 2.2. Even more, the slope of the blue line (so growth of trend TFP after the Great Recession) is lower than the slope of the red line (so growth of trend TFP before the Great Recession), thus the loss in aggregate productivity due to the slowdown in productivity growth seems to be still growing. Of course the results here have to be taken with a grain of salt, as the HP-filter is atheoretic and the separation of business cycle fluctuations and longer-run growth might not be perfectly accurate (see for instance the critique in Comin and Gertler (2006) mentioned in the introductory chapter of this dissertation), however the main observation of a slowdown in longer-run technological progress during the Great Recession stands.

The present paper argues that the outward shift in the Beveridge Curve in consequence of a severe negative matching efficiency shock and the slowdown in trend growth of TFP, both observed during the Great Recession, are causally linked. The next section presents a model, where the lower matching efficiency implied by the outward shift of the Beveridge Curve leads to a higher entry barrier for outside firms, which reduces the innovative pressure on incumbent firms and thus reduces aggregate TFP. Estimating the model, it turns out that the negative matching efficiency shock can explain a major part of the drop in endogenous TFP growth during the Great Recession. The permanent loss in TFP amasses to an over 0.6% lower TFP in the beginning of 2019.

2.3 The model

The model proposed here includes a labor market with search friction as for instance in Mortensen and Pissarides (1994). In particular, a matching function is assumed that produces matches between firm vacancies and unemployed workers. The matching function implies that a certain firm vacancy cannot be filled with the first unemployed worker that is met on the labor market, but that there is a probability this worker is no match for the firm and search has to continue. Continuing job search is assumed to be costly, thus the lower the matching efficiency the higher the hiring costs. Furthermore, there is an R&D and technology adoption sector as in Anzoategui et al. (2019), Benigno and Fornaro (2017) or Comin and Gertler (2006), where new ideas do not instantly improve productivity but have to be adopted over time beforehand. This mechanism allows short-run business cycle shocks, like for instance matching efficiency shocks, to have long-run implications, as short-run shocks affect innovation today, but the effect of innovation on actual productivity only falls in to place over the long-term, because new technologies first have to diffuse through the firm sector.

Additionally, there is a firm sector with Schumpeterian competition between outsiders and incumbents for the position in the market, which always goes to the firm with the highest productivity. A quality ladder as in Grossman and Helpman (1991) is assumed, where a new adopted technology increases product quality. An alternative specification to vertical technological progress, as implied by the quality ladder assumption, would be horizontal technological progress like in a love for variety model, where there is a growing number of firms and each firm needs a patent to come into existence. Both specifications are commonly used in the literature and have similar implications for technological progress. The reason for favoring vertical technological progress here is that labor and productivity should both be concerning one and the same firm if one wants to study the effect of labor market conditions on technological progress. If labor is employed by a growing number of firms and the firm number is the growth inducing factor, then either aggregate labor has to constantly grow as well and labor productivity stays constant, which does not fit the data, or decrease per firm to allow a constant aggregate unemployment rate and growing labor productivity on the balanced growth path, but implies increasing labor turnover along the balanced growth path, which again does not fit the data. Consequently, vertical growth fits the data better and is the more natural choice for the matter at hand, but otherwise is without loss of generality. Schumpeterian competition implies that only the firm with the highest rung on the quality ladder can stay in the market, while low quality firms have to leave the market[5]. The notion of more competition stirring up technological progress is well known to the literature[6] and is incorporated in the present model as competition for the position as incumbent.

The labor market friction imposes an entry barrier to the outsiders, who are assumed to have no worker stock in contrast to the incumbents as in Mortensen (2005). So if hiring workers becomes more difficult because matching efficiency declines, outsiders will face a higher entry barrier and thus a lower incentive to become the next incumbent, which reduces innovative pressure on the current incumbents and gives them an incentive to lower their innovation spending as well. In consequence, aggregate innovation spending and long-run productivity decrease after matching efficiency on the labor market declines.

2.3.1 Labor market

Assume a standard matching function of the form

$$m(u_t, v_t) = \mu_t u_t^{\xi} v_t^{1-\xi}, \quad \xi \in (0, 1), \tag{2.1}$$

where u_t is the number of unemployed, v_t is the number of vacancies and μ_t is the matching efficiency, which is given by

$$\mu_t = \bar{\mu} \exp(f_t), \quad \bar{\mu} > 0, \tag{2.2}$$

where $\bar{\mu}$ is the steady state matching efficiency and f_t are short-run fluctuations of the matching efficiency, which follow an autoregressive process of the form

$$f_t = \rho^f f_{t-1} + \varepsilon_t^f, \quad \rho^f \in (0, 1), \tag{2.3}$$

[5]see Olley and Pakes (1996)

[6]for further evidence see Arrow (1962), Nickell (1996) and Blundell et al. (1995)

with ε_t^f an i.i.d. aggregate shock to the matching efficiency. Positive shocks lead to an inward shift of the Beveridge Curve with higher matching efficiency, while negative ones lead to an outward shift with lower matching efficiency (higher matching efficiency leads to more matches for a given number of vacancies and unemployed, thus in the equilibrium a given number of vacancies is associated with fewer unemployed and the new Beveridge Curve lies below the old one, so shifted inwards, and vice versa). This paper follows Furlanetto and Groshenny (2016) in interpreting the matching efficiency shock as a "take all shock" or "Solow residual" of the matching function for any structural mismatches on the labor market that remain unexplained by the rest of structural shocks included in the model. Define labor market tightness $\theta_t = \frac{v_t}{u_t}$, then the probability of filling a vacancy for the firms is

$$\Phi^v(\theta_t) = \frac{m(u_t, v_t)}{v_t} = \mu_t \left(\frac{u_t}{v_t}\right)^{\xi} = \mu_t \left(\frac{1}{\theta_t}\right)^{\xi} \tag{2.4}$$

and the probability of finding a job for unemployed is given by

$$\Phi^j(\theta_t) = \frac{m(u_t, v_t)}{u_t} = \mu_t \left(\frac{v_t}{u_t}\right)^{1-\xi} = \mu_t \theta_t^{1-\xi} = \theta_t \Phi^v(\theta_t). \tag{2.5}$$

The probability of filling a posted job vacancy $\Phi^v(\theta_t)$ is crucial for the entry decision of outside firms and thus fulfills an important role for technological progress as explained further below. Especially note that $\frac{\partial \Phi^v(\theta_t)}{\partial \mu_t} > 0$, so an exogenous increase in matching efficiency increases the probability of filling a posted vacancy for firms.

In every period there is Nash bargaining about the real wage between workers and firms. Let S_t denote the surplus from having a job for workers and J_t the surplus of having a worker for firms. Then the real wage w_t is found by maximizing the total value of the bargain

$$w_t = argmax(S_t)^{\tau}(J_t)^{1-\tau}, \quad \tau \in (0, 1), \tag{2.6}$$

where τ is the bargaining power of workers. Denote the marginal revenue product of labor for intermediate firms as Θ_t and the unemployment benefit for unemployed workers as b_t, then J_t is given by the marginal revenue product of labor minus the real wage, while the value of having a job is the difference between receiving the real wage w_t or only unemployment benefits b_t, so

$$J_t = \Theta_t - w_t \tag{2.7}$$

$$S_t = w_t - b_t. \tag{2.8}$$

Solving the Nash bargaining problem from above, the usual sharing rule obtains

$$w_t = \tau\Theta_t + (1-\tau)b_t, \tag{2.9}$$

so the real wage will be close to the unemployment benefit, if the bargaining power of workers is low and close to the marginal revenue product of workers, if their bargaining power is high.

2.3.2 R&D sector

The R&D sector produces new unadopted (so not yet ready to increase firm productivity) ideas R_t by employing real research effort X_t, which is paid as a transfer to the household sector. The production function for new unadopted ideas reads

$$R_t = \chi\left(\frac{X_t}{q_t}\right)^{1-\kappa}, \quad \chi > 0, \kappa \in (0,1), \tag{2.10}$$

where q_t is the economy's TFP level. That a higher TFP level negatively affects idea production is required for the existence of a balanced growth path and reflects the idea that in advanced economies it becomes increasingly difficult to push forward the technological frontier. As a consequence of growing productivity, there are more means to invest in research in each period. So without any counteracting variable, research and thus productivity would explode. For instance Comin and Gertler (2006) explicitly model a congestion externality for research spending, in particular they assume that higher aggregate research spending reduces the productivity of individual research spending. Alternatively, Anzoategui et al. (2019) see the congesting factor in aggregate skilled labor that is used in the production of new ideas. All of these congesting factors are ultimately related to aggregate productivity, the present paper stays agnostic about the exact R&D process and thus uses aggregate productivity as a proxy for what ever might hinder research efficiency.

The R&D sector sells new unadopted ideas to the licenser at competitive price p_t^R, so the profit maximization problem reads

$$\max_{X_t} \Gamma_t = p_t^R R_t - X_t, \tag{2.11}$$

subject to (2.10). The first order condition then reads

$$(1-\kappa)\chi\frac{p_t^R}{q_t} = \left(\frac{X_t}{q_t}\right)^{\kappa}, \tag{2.12}$$

so the optimal input amount of research effort depends on the price for new unadopted ideas.

2.3.3 Licenser

The licenser holds and accumulates the stock of unadopted ideas $\mathcal{U}_t$ by buying new unadopted ideas R_t from the R&D sector and selling licenses for technology adoption to the technology adoption sector that may result in Δ_t^A of the unadopted ideas becoming adopted technologies, if the technology adopter succeeds in adopting these particular technologies. In consequence, the stock of unadopted ideas evolves according to

$$\mathcal{U}_t = (1-\delta^{\mathcal{U}})\mathcal{U}_{t-1} + R_t - \Delta_t^A, \quad \delta^{\mathcal{U}} \in (0,1), \tag{2.13}$$

where $\delta^{\mathcal{U}}$ is the obsolescence rate of unadopted ideas. The licenser grants a license to the technology adopters for the usage of an unadopted idea at competitive price $p_t^{\mathcal{U}}$, so the maximization problem of expected lifetime profits for the licenser reads

$$\max_{R_t} E_t \sum_{s=0}^{\infty} \Lambda_{t,t+s}\Xi_{t+s} = E_t \sum_{s=0}^{\infty} \Lambda_{t,t+s}\left[p_{t+s}^{\mathcal{U}}\mathcal{U}_{t+s-1} - p_{t+s}^R R_{t+s}\right], \tag{2.14}$$

with E_t the expectations operator and $\Lambda_{t,t+s}$ the stochastic discount factor between periods t and $t+s$, while subject to (2.13). Consequently, the FOC for the licenser reads

$$p_t^R = E_t\Lambda_{t,t+1}p_{t+1}^{\mathcal{U}}, \tag{2.15}$$

so the expected license price is equal to the current price for new unadopted ideas.

2.3.4 Technology adopter

The technology adopter buys a license for adoption of an unadopted technology in period t from the licenser at price $p_t^{\mathcal{U}}$. The probability of succeeding to adopt a certain technology and thus the speed of diffusion of unadopted ideas into adopted ideas is given by $\phi(\Upsilon_t, q_t) = \gamma\left(\frac{\Upsilon_t}{q_t}\right)^{1-\varphi}$, with $\gamma > 0, \varphi \in (0,1)$, where Υ_t is real adoption effort modeled as a real resource cost paid to the household sector. Again, with the same reasoning as for the R&D sector, the TFP level shows up in the denominator to guarantee the existence of a balanced growth path, as in a growing economy there are more means to spend on adoption in every subsequent period and without any counteracting variable, the growth path would be explosive. Including the aggregate TFP level in the denominator of the diffusion speed reflects the idea that more advanced technologies are more difficult to adopt. New adopted ideas Δ_t^A thus are given by

$$\Delta_t^A = \gamma \left(\frac{\Upsilon_t}{q_t} \right)^{1-\varphi} \mathcal{U}_{t-1}. \tag{2.16}$$

Newly adopted ideas are sold to intermediate goods producing firms at competitive price p_t^A, so the profit maximization problem of the technology adopter reads

$$\max_{\Upsilon_t, \mathcal{U}_{t-1}} \Omega_t = p_t^A \Delta_t^A - p_t^{\mathcal{U}} \mathcal{U}_{t-1} - \Upsilon_t \tag{2.17}$$

subject to (2.16), yielding the following FOC:

$$\frac{p_t^A}{q_t}(1-\varphi)\gamma \mathcal{U}_{t-1} = \left(\frac{\Upsilon_t}{q_t} \right)^{\varphi} \tag{2.18}$$

$$\gamma \left(\frac{\Upsilon_t}{q_t} \right)^{1-\varphi} = \frac{p_t^{\mathcal{U}}}{p_t^A} \tag{2.19}$$

Equation (2.18) gives the optimal input relation between adoption effort and unadopted ideas at a given price p_t^A, where a higher ratio of adoption spending compared to the stock of unadopted ideas has to be associated with a higher price for adopted technologies. Equation (2.19) gives the optimal adoption effort depending on the price ratio between unadopted and adopted technologies, where with a higher price of unadopted ideas in relation to adopted ideas, the technology adopter will choose to increase the adoption rate rather than to acquire new unadopted ideas.

2.3.5 Final goods sector

The final goods producer uses capital K_{t-1} and intermediate goods $z_{i,t}$ from a continuum of intermediate firms with mass 1 as inputs to produce final output Y_t. The production function for final goods reads

$$Y_t = \frac{1}{1-\alpha} \left[\int_0^1 z_{i,t}^{1-\alpha} di \right] K_{t-1}^{\alpha}, \quad \alpha \in (0,1). \tag{2.20}$$

Intermediate goods are bought from intermediate goods producers at price $p_{i,t}^z$, while capital is rented from the households at rental rate r_t^K, so the profit maximization problem of the final goods producer reads

$$\max_{z_{i,t},K_{t-1}} D_t^f = Y_t - \int_0^1 p_{i,t}^z z_{i,t} di - r_t^K K_{t-1}, \tag{2.21}$$

which yields the following first order conditions

$$z_{i,t} = (p_{i,t}^z)^{-\frac{1}{\alpha}} K_{t-1} \tag{2.22}$$

$$r_t^K = \frac{\alpha}{1-\alpha} \left[\int_0^1 z_{i,t}^{1-\alpha} di \right] K_{t-1}^{\alpha-1}. \tag{2.23}$$

Equation (2.22) says that the demand for intermediate goods negatively depends on their price, where the demand elasticity is the inverse production elasticity of intermediate goods, but positively on capital demand. Equation (2.23) implies that the real capital rental rate will be equal to the marginal product of capital in the optimum.

2.3.6 Intermediate firms

An individual intermediate firm i is the monopolistic supplier of intermediate good $z_{i,t}$. The intermediate good is produced according to the production function

$$z_{i,t} = q_{i,t} n_{i,t}, \tag{2.24}$$

where $q_{i,t}$ is the productivity level and $n_{i,t}$ the labor input of firm i. The productivity level of firm i is given by

$$q_{i,t} = \lambda^{A_{i,t-1}} exp(e_t), \quad \lambda > 1, \tag{2.25}$$

where $A_{i,t-1}$ is the stock of adopted technologies firm i has acquired with accumulation constraint

$$A_{i,t} = A_{i,t-1} + \Delta_{i,t}^A. \tag{2.26}$$

and e_t are exogenous aggregate TFP fluctuations with the autoregressive law of motion

$$e_t = \rho^q e_{t-1} + \varepsilon_t^q, \quad \rho^q \in (0,1), \tag{2.27}$$

where ε_t^q is an i.i.d. aggregate TFP shock that affects the productivity of all individual intermediate goods firms at the same time (so the shock is not firm specific, but a shock to overall productivity). Incumbent intermediate firms have a stock of workers following the law of motion

$$n_{i,t} = (1 - \delta_t^j) n_{i,t-1} + \Phi^v(\theta_t) v_{i,t}, \tag{2.28}$$

where $\Phi^v(\theta_t)v_{i,t}$ are the vacancies that are filled with a worker, thus the inflow of new workers, and δ_t^j is the exogenous separation rate given by

$$\delta_t^j = \bar{\delta}^j exp(d_t), \quad \bar{\delta}^j \in (0,1), \tag{2.29}$$

with d_t denoting exogenous fluctuations in the separation rate following the autoregressive law of motion

$$d_t = \rho^j d_{t-1} + \varepsilon_t^j, \quad \rho^j \in (0,1), \tag{2.30}$$

with ε_t^j an exogenous i.i.d. shock to the separation rate. Posting a vacancy incurs a vacancy cost of ς_t, where $\frac{\varsigma_t}{q_t} = \bar{\varsigma}$ and $\bar{\varsigma} > 0$, which is necessary for the existence of a steady state in detrended form and reflects the idea that a higher technology level makes job descriptions more complex and thus increases the cost of posting a vacancy, as otherwise, with increasing productivity and profits, hiring and thus total labor would increase along the balanced growth path. In every period, the intermediate firm and outside competitors can invest in their future productivity level and buy new adopted technologies from the technology adopter at price p_t^A and add them to their stock of technologies.

Assume further Schumpeterian creative destruction: Only the firm with the highest quality level for a certain intermediate product i survives. The current level of quality can be copied without any cost by everyone, while quality improvements are only attained by buying new adopted technologies from the technology adopter. The incumbent firm faces competition for its position as the incumbent by outside competitors: If it does not improve its own quality level enough every period, outsiders will attain a higher quality level and destroy the incumbent, leaving it with zero profits for the rest of time. Looking at the entry condition for the outside competitors, their optimal quality improvement decision per period can be obtained: For entry, outsiders will have to pay innovation cost $p_t^A \Delta_{i,t}^A$ in order to improve the technology level. Furthermore, outsiders have a structural disadvantage compared to incumbents as they are assumed to not have any worker stock, so they need to hire the equivalent of the worker stock of any incumbent firm they want to replace (by symmetry the i index can be dropped) to be able to produce. This of course is costly and depends on the current situation of the labor market. Gaining the position of the incumbent yields the expected lifetime profits of being the incumbent in the future. Period profits are revenue from selling intermediate goods at price $p^z_{i,t}$ minus period labor and hiring costs, as well as potential innovation costs for staying in the market for one period longer. Thus, define lifetime profits in the Bellman type equation

$$\mathcal{M}_{i,t} = p^z_{i,t} z_{i,t} - w_t n_{i,t} - \varsigma_t v_{i,t} - p^A_t \Delta^A_{i,t} + E_t \Lambda_{t,t+1} \mathcal{M}_{i,t+1}. \tag{2.31}$$

As from a certain firm's point of view, may it be current incumbent or outsider, all other firms are assumed to behave optimally and only the firm with the highest quality $q_{\tilde{i},t} = \max q_{i,t}$ can be the incumbent, the i index can be replaced by $\tilde{i}$ in each firm branch i for the relevant decision about which innovation spending will win the innovation contest.

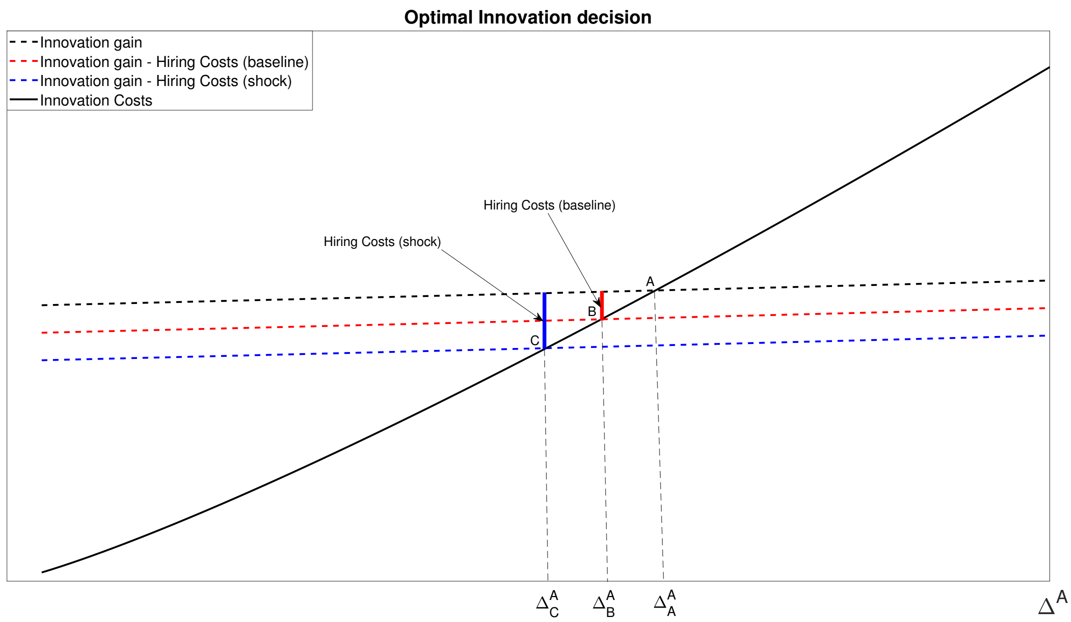
However, outsiders would have to pay additional hiring costs in order to become incumbents. Recall that the expected worker stock current incumbents would have at their disposal in the next period is $E_t(1 - \delta^j_{t+1})n_t$ and in order to replace the current incumbent as the producing firm, $E_t \frac{(1-\delta^j_{t+1})n_t}{\Phi^v(\theta_t)}$ vacancies are required to build up this worker stock as a potential entrant. Free entry to the innovation contest dictates that a winning outside firm would always have to be at the indifference point between contesting and not contesting. Spending less is a guaranteed loss in the innovation contest, as a competitor could spend a little bit more and win with a positive gain from contesting, spending more yields a negative value of becoming the incumbent, as the gain of being the future incumbent then would be lower than the effort to win the contest. The following term gives this indifference point for outside firms:

$$p^A_t \Delta^A_{\tilde{i},t} + E_t \left(\varsigma_{t+1} \frac{(1 - \delta^j_{t+1}) n_t}{\Phi^v(\theta_t)} \right) \stackrel{!}{=} E_t \Lambda_{t,t+1} \mathcal{M}_{\tilde{i},t+1}, \tag{2.32}$$

so indifference between innovating or not innovating is reached at the point where expected entry costs (the sum of innovation and hiring costs on the left-hand side) equal expected entry gain (the expected discounted future lifetime profits on the right-hand side). Here the influence of matching efficiency on the innovation decision becomes evident: The probability of finding a worker enters the denominator of the entry costs on the left-hand side, so if it becomes harder to acquire new workers for possible entrants, it will reduce their gain from innovating. A negative matching efficiency shock, by being persistent, also reduces the expected discounted future profits on the right hand side, as it will become harder to acquire workers in the future, so innovation becomes less attractive and potential entrants would choose to innovate less and thus the innovative pressure on the incumbents decreases.

Condition (2.32) imposes a lower bound on the innovation decision of the incumbents, as spending less always leads to a loss in the innovation contest. If for instance current incumbents innovate less, an entrant will replace them and leave them with zero profits. Would the current incumbents like to innovate more than that at this point, as they have to pay lower hiring costs than outsiders and thus have more means to invest in technology? Under the model assumptions made here, the answer is no. Figure 2.3 for simplicity assumes that a matching efficiency shock is a one-time event and shows that current incumbents will choose their innovation spending according to the indifference point of the outside firms. As becomes ev-

Figure 2.3: This figure schematically plots innovation cost $p_t^A \Delta_t^A$ (black solid line) and gain $E_t \Lambda_{t,t+1} \mathcal{M}_{t+1}$ (black dashed line) depending on the amount of innovation Δ_t^A. The hiring costs shift the innovation gain of potential entrants downwards (red dashed line). If there were no hiring costs, optimal innovation is at point A for both entrants and incumbents and with zero profits for both. With hiring costs, optimal innovation is at point B for both entrants and incumbents, but with positive profits for incumbents (red solid line). A negative one-time shock to matching efficiency shifts the gain curve downwards (blue dashed line) and leads to lower innovation at point C with higher profits for incumbents (blue solid line).



ident from figure 2.3, in order to have a unique interior optimum, the innovation cost curve has to be at first below the innovation gain curve, but the slope of the cost curve has to be higher than the slope of the gain curve to get an intersection point, where further innovation does not yield any more profit. With no hiring costs, incumbents and potential entrants are equal and the optimal innovation decision would be at point A. However, the hiring costs, being independent of the innovation decision, shift the innovation gain of potential entrants down, so the intersection of innovation gain and costs is at point B, where outsiders are at their indifference point. At point B, incumbents have positive intertemporal profits, but any movement to the right, so more innovation, decreases these profits. This is because the intertemporal profits made at this point are equal to the distance between the cost and gain curve, which by construction is equal to the distance between the gain curves with and without hiring costs (blue solid line for the case without matching efficiency shock, red solid line for the event of a one-time matching efficiency shock). The intertemporal profits current incumbents can generate are thus equal to the additional hiring costs outsiders would incur, which are independent of the innovation decision of the current incumbent. Consequently, increasing innovation spending from this point onward will always reduce intertemporal profits and is thus not optimal. So incumbents will also choose point B as their optimal innovation decision. Consequently, the optimal innovation decision is exogenously given by the competition between incumbents and potential entrants. A negative matching efficiency shock increases the hiring costs for entering firms and shifts the innovation gain curve downwards, leading to less innovation at point C.

In the optimum, the current incumbent will always stay the incumbent, as in contrast to outsiders it has a strictly positive continuation value and can always choose to spend one infinitely small increment more on innovation than outsiders and win the innovation race. Therefore, the expected lifetime profit optimization problem of intermediate firm i reads

$$\max_{p^z_{i,t}} E_t \sum_{s=0}^{\infty} \Lambda_{t,t+s} D^{im}_{i,t+s} = E_t \sum_{s=0}^{\infty} \Lambda_{t,t+s} (p^z_{i,t+s} z_{i,t+s} - w_{t+s} n_{i,t+s} - \varsigma_{t+s} v_{i,t+s} - p^A_{t+s} \Delta^A_{\tilde{i},t+s}) \tag{2.33}$$

subject to equations (2.24)-(2.30). Solving this yields the optimal pricing behavior of the intermediate firm given by

$$p^z_{i,t} = \frac{1}{1-\alpha} \left[\frac{w_t}{q_t} + \frac{\bar{\varsigma}}{\Phi^v(\theta_t)} - E_t \Lambda_{t,t+1} (1 - \delta^j_{t+1}) \frac{\bar{\varsigma}}{\Phi^v(\theta_{t+1})} (1 + g^q_{i,t+1}) \right], \tag{2.34}$$

where $g^q_{i,t} = \frac{q_{i,t} - q_{i,t-1}}{q_{i,t-1}}$ is the productivity growth rate for firm i. Equation (2.34) has the usual interpretation that monopolist $i's$ optimal price will be a markup on the real marginal production costs.

From the setup of the intermediate sector above, the marginal revenue product of labor for firm i used in the wage bargaining (2.9) reads

$$\Theta_{i,t} = p^z_{i,t} q_{i,t}. \tag{2.35}$$

2.3.7 Government sector

The government collects a lump-sum tax T_t from the households and finances unemployment benefits with it, so the government budget reads

$$b_t u_t = T_t. \tag{2.36}$$

Assume further for simplicity that the government keeps the unemployment benefits in a fixed ratio to the real wage, so

$$b_t = (1-\omega) w_t, \quad \omega \in (0,1). \tag{2.37}$$

Though the assumptions here are simplifying, they do not clash with reality too much. Unemployment benefits are persistently around roughly 1/3 of the average wage for the U.S., so assuming a constant ratio between b_t and w_t seems to be a good approximation for reality concerning the purpose of the model at hand.

2.3.8 Household sector

The representative household maximizes the following utility function

$$U_t = E_t \sum_{s=0}^{\infty} exp(g_t) \beta^s \ln(C_t), \quad \beta \in (0,1), \tag{2.38}$$

where U_t denotes lifetime utility, $g_t = \rho^g g_{t-1} + \varepsilon^g_t, \rho^g \in (0,1)$ are consumer preference fluctuations with ε^g_t an i.i.d. consumer preference shock and C_t is consumption, subject to the budget constraint given in any period by (by symmetry intermediate firms are identical and the i index on intermediate firm residual profits can be dropped)

$$C_t + I_t + T_t = w_t n_t + b_t u_t + r^K_t K_{t-1} + \Gamma_t + \Xi_t + \Omega_t + D^{im}_t + D^f_t + \varsigma_t v_t + X_t + \Upsilon_t, \tag{2.39}$$

where I_t denotes investment. Capital accumulation is given by

$$K_t = (1 - \delta^K)K_{t-1} + I_t, \quad \delta^K \in (0, 1). \tag{2.40}$$

The labor force is normalized to one such that

$$u_t + n_t = 1. \tag{2.41}$$

Consequently, the FOCs of utility maximization yield the usual Euler equation, which gives the optimal consumption-savings decision

$$C_t^{-1} = E_t \beta \frac{exp(g_{t+1})}{exp(g_t)} (1 + r_{t+1}^K - \delta^K) C_{t+1}^{-1}. \tag{2.42}$$

2.3.9 Aggregate resource constraint

As ex-post all intermediate firms will behave exactly the same and the mass of firms is normalized to 1, individual quantities will equal aggregate quantities. Putting together the resource constraints of every sector described above yields the aggregate resource constraint given by

$$Y_t = C_t + I_t. \tag{2.43}$$

2.3.10 Equilibrium

By symmetry all individual intermediate firms will behave the same, so the i-index can be dropped. Summing up, an aggregate equilibrium is given by the sequence of variables

$$\Big\{ \theta_{t+s}, \mu_{t+s}, v_{t+s}, u_{t+s}, f_{t+s}, w_{t+s}, \Theta_{t+s}, b_{t+s}, p_{t+s}^z, q_{t+s}, R_{t+s}, X_{t+s}, p_{t+s}^R, \mathcal{U}_{t+s}, p_{t+s}^{\mathcal{U}}, \Lambda_{t,t+s}, r_{t+s}^K, \Delta_{t+s}^A, \Upsilon_{t+s}, p_{t+s}^A, A_{t+s}, Y_{t+s}, z_{t+s}, K_{t+s}, n_{t+s}, e_{t+s}, \varsigma_{t+s}, \delta_{t+s}^j, d_{t+s}, g_{t+s}^q, \mathcal{M}_{t+s}, I_{t+s}, C_{t+s}, g_{t+s} \Big\}_{s=0}^{\infty}$$

that fulfill the following set of equilibrium conditions

$$\Phi^v(\theta_t) = \mu_t \left(\frac{1}{\theta_t} \right)^{\xi} \tag{2.44}$$

$$\theta_t = \frac{v_t}{u_t} \tag{2.45}$$

$$\mu_t = \bar{\mu}\exp(f_t) \tag{2.46}$$

$$f_t = \rho^f f_{t-1} + \varepsilon_t^f \tag{2.47}$$

$$w_t = \tau\Theta_t + (1-\tau)b_t \tag{2.48}$$

$$\Theta_t = p_t^z q_t \tag{2.49}$$

$$b_t = (1-\omega)w_t \tag{2.50}$$

$$R_t = \chi\left(\frac{X_t}{q_t}\right)^{1-\kappa} \tag{2.51}$$

$$(1-\kappa)\chi\frac{p_t^R}{q_t} = \left(\frac{X_t}{q_t}\right)^{\kappa} \tag{2.52}$$

$$\mathcal{U}_t = (1-\delta^{\mathcal{U}})\mathcal{U}_{t-1} + R_t - \Delta_t^A \tag{2.53}$$

$$p_t^R = E_t\Lambda_{t,t+1}p_{t+1}^{\mathcal{U}} \tag{2.54}$$

$$\Lambda_{t,t+1} = E_t\frac{1}{1+r_{t+1}^K-\delta^K} \tag{2.55}$$

$$\Delta_t^A = \gamma\left(\frac{\Upsilon_t}{q_t}\right)^{1-\varphi}\mathcal{U}_{t-1} \tag{2.56}$$

$$\frac{p_t^A}{q_t}(1-\varphi)\gamma\mathcal{U}_{t-1} = \left(\frac{\Upsilon_t}{q_t}\right)^{\varphi} \tag{2.57}$$

$$p_t^A\gamma\left(\frac{\Upsilon_t}{q_t}\right)^{1-\varphi} = p_t^{\mathcal{U}} \tag{2.58}$$

$$A_t = A_{t-1} + \Delta_t^A \tag{2.59}$$

$$Y_t = \frac{1}{1-\alpha}z_t^{1-\alpha}K_{t-1}^{\alpha} \tag{2.60}$$

$$z_t = (p_t^z)^{-\frac{1}{\alpha}}K_{t-1} \tag{2.61}$$

$$r_t^K = \frac{\alpha}{1-\alpha}z_t^{1-\alpha}K_{t-1}^{\alpha-1} \tag{2.62}$$

$$z_t = q_t n_t \tag{2.63}$$

$$q_t = \lambda^{A_{t-1}}exp(e_t) \tag{2.64}$$

$$e_t = \rho^q e_{t-1} + \varepsilon_t^q \tag{2.65}$$

$$\frac{\varsigma_t}{q_t} = \bar{\varsigma} \tag{2.66}$$

$$\delta_t^j = \bar{\delta}^j exp(d_t) \tag{2.67}$$

$$d_t = \rho^j d_{t-1} + \varepsilon_t^j \tag{2.68}$$

$$n_t = (1-\delta_t^j)n_{t-1} + \Phi^v(\theta_t)v_t \tag{2.69}$$

$$p_t^z = \frac{1}{1-\alpha}\left[\frac{w_t}{q_t} + \frac{\bar{\varsigma}}{\Phi^v(\theta_t)} - E_t\Lambda_{t,t+1}(1-\delta_{t+1}^j)\frac{\bar{\varsigma}}{\Phi^v(\theta_{t+1})}(1+g_{t+1}^q)\right] \tag{2.70}$$

$$g_t^q = \frac{q_{i,t}-q_{i,t-1}}{q_{i,t-1}} \approx \ln(q_t) - \ln(q_{t-1}) = \ln(\lambda)\Delta_{t-1}^A + \ln(e_t) - \ln(e_{t-1}) \tag{2.71}$$

$$E_t\left(p_t^A\Delta_t^A + \varsigma_{t+1}\frac{(1-\delta_{t+1}^j)n_t}{\Phi^v(\theta_t)}\right) = E_t\Lambda_{t,t+1}\mathcal{M}_{t+1} \tag{2.72}$$

$$\mathcal{M}_t = p_t^z z_t - w_t n_t - \varsigma_t v_t - p_t^A\Delta_t^A + E_t\Lambda_{t,t+1}\mathcal{M}_{t+1} \tag{2.73}$$

$$K_t = (1-\delta^K)K_{t-1} + I_t \tag{2.74}$$

$$u_t + n_t = 1 \tag{2.75}$$

$$C_t^{-1} = \beta\frac{exp(g_{t+1})}{exp(g_t)}E_t(1 + r_{t+1}^K - \delta^K)C_{t+1}^{-1} \tag{2.76}$$

$$g_t = \rho^g g_{t-1} + \varepsilon_t^g \tag{2.77}$$

$$Y_t = C_t + I_t \tag{2.78}$$

The economy has a balanced growth path, where all growing variables grow at a common rate of $g_{t-1}^{qt} = \ln(\lambda)\Delta^{A_{t-1}}$. In the appendix, this trend growth rate, detrended form and steady state of the model are derived, which are used to numerically solve the model using Dynare[7]. Especially note, that inserting the production function of intermediate goods producers into the production function of final goods producers yields the aggregate production function of the form

$$Y_t = \frac{1}{1-\alpha}\left(q_t n_t\right)^{1-\alpha} K_{t-1}^{\alpha}, \tag{2.79}$$

so q_t can be interpreted as total factor productivity with labor augmenting technological progress.

2.4 Bringing the model to the data

In this section, some of the model parameters are calibrated externally, while the crucial parameters are estimated using Bayesian techniques. The focus lies on uncovering the long-run effects on endogenous technological progress that the strong decline in matching efficiency during the Great Recession had. As an additional robustness check, it is checked if aggregate shocks to job destruction, TFP and consumer preferences mitigated the impact of the strong decline in matching efficiency on endogenous technological progress. The first part of the section discusses the calibration or estimation procedure for the model parameters, while the second part discusses the estimated effect of matching efficiency shocks on endogenous TFP growth.

[7] see Adjemian et al. (2011)

2.4.1 Calibration and parameter estimation

The scaling parameters of the model are not estimated, but calibrated such that some crucial steady state values fit observational means from the data. Table 2.1 summarizes the parameters calibrated and the reasons for the chosen values: The

Table 2.1: Externally calibrated parameters

Parameter	Value	Source
$\bar{\mu}$	0.89	Fitting the mean job finding rate (Sedláček (2014))
ω	0.61	U.S. mean unemployment benefits to wage ratio
χ	0.88	Fit mean R&D to GDP ratio
$\delta^{\mathcal{U}}$	0.03	Technology obsolescence rate (Comin and Gertler (2006))
β	0.98	standard calibration
γ	0.395	Fit mean TFP growth rate
δ^{K}	0.025	standard calibration
λ	1.03	Technology hazard rate (Basu and Fernald (1997))
$\bar{\varsigma}$	21	Fitting mean vacancy rate
$\bar{\delta^{j}}$	0.043	Job destruction rate (Sedláček (2014))

steady state matching efficiency is calibrated such that the steady state unemployment rate from the model matches the mean unemployment rate of about 6% observed in the data and matches a job finding rate of about 60% as in Sedláček (2014). Sedláček (2014) estimates the average job separation rate for the U.S. to be about 4.2% , so $\bar{\delta^{j}} = 0.042$. The fraction of unemployment benefits to the average wage is about 39% for the U.S., so ω is set to 0.61. Following Comin and Gertler (2006), the obsolescence rate of unadopted ideas is about 3%, so $\delta^{\mathcal{U}} = 0.03$. Concerning the technological hazard rate[8] λ, Basu and Fernald (1997) find it to be around 1.03. Finally, the values of the discount rate ($\beta = 0.98$) and the depreciation rate of capital ($\delta^{K} = 0.025$) are set to widely used standard values in the literature. The scaling parameters χ, γ and $\bar{\varsigma}$ are calibrated such that the steady state values of the R&D to GDP ratio, TFP growth and vacancy rate match their respective mean in the data. The mean R&D ratio in the data is about 2.84%, the mean TFP growth rate about 1.13% and the mean vacancy rate about 3.08%.

The remaining parameters and shock standard errors are then estimated using Bayesian methods. There are 5 observables: The TFP growth rate[9], the vacancy

[8] The interpretation of λ as a hazard rate comes from the idea that each climb on the quality ladder replaces older vintages of a certain technology by newer ones, which increases productivity.

[9] TFP is adjusted to be in line with the assumption of purely labor augmenting technological progress as in the model and not labor and capital augmenting as assumed by Fernald (2012-2019), so the residual between output growth and input factor growth that is defined as TFP growth by Fernald (2012-2019) is multiplied by $\frac{1}{1-\alpha}$. For the derivation see the appendix.

and unemployment rates as defined above, the output growth rate (growth of output per capita) provided by Fernald (2012-2019) and the R&D to GDP ratio in percent provided by the FRED (2020). The exogenous variable ι^{xy} has the usual interpretation of a measurement error in the R&D to GDP ratio, because R&D expenditures are notoriously hard to measure, as large parts of private research spending that do not lead to success remain unaccounted for. The introduction of a measurement error allows the model estimation to be more flexible with respect to such mismeasurements. Furthermore, the inclusion of the measurement error in addition to the four structural shocks eliminates stochastic singularity that occurs, if there are fewer structural shocks than observed variables. Consequently, the observation equations in terms of the model variables read (where tildes denote detrended variables)

$$vacancy\_rate_t = \frac{v_t}{v_t + u_t} \cdot 100 \tag{2.80}$$

$$unemployment\_rate_t = \frac{u_t}{u_t + n_t} \cdot 100 \tag{2.81}$$

$$TFP\_growth_t = (g^{qt}_{t-1} + e_t - e_{t-1}) \cdot 400 \tag{2.82}$$

$$output\_growth = (g^{qt}_{t-1} + e_t - e_{t-1} + \ln(\tilde{Y}_t) - \ln(\tilde{Y}_{t-1})) \cdot 400 \tag{2.83}$$

$$R\&D\_ratio = \left(\frac{\tilde{X}}{\tilde{Y}} + \iota^{xy}\right) \cdot 100. \tag{2.84}$$

The choice of prior distributions follows mainly the propositions of Smets and Wouters (2003). The priors for the persistence parameters ρ^f, ρ^q and ρ^j accordingly follow a Beta distribution with mean 0.85 and standard error 0.05. Preestimation of the persistence parameter ρ^g shows that it is much lower than the persistence parameters for the other shock processes. As this paper wants to remain agnostic concerning the shock persistence, the prior mean is adjusted accordingly to be only about 1/3 of the other parameters, which appears to be more accurate judging by the preestimation. Also following Smets and Wouters (2003), the shock standard error priors follow an Inverse Gamma distribution with standard error 2, the respective means are obtained by preestimations. The parameters ξ, κ, α, φ and τ are crucial for the reaction of labor market variables and technological progress to matching efficiency shocks, therefore they are especially interesting to be estimated. The latter five parameters all should lie between 0 and 1, so a Beta prior is chosen. There are concrete estimates of the parameters in the literature, so the priors are chosen to be narrow around these values with a standard error of 0.025. Griliches (1990) estimates the parameter κ to be around 0.3, so the prior mean for this parameter is chosen to be 0.3. Sedláček (2014) estimates ξ to be about 0.567 and τ to be around 0.204, so the prior means are chosen accordingly. Anzoategui et al. (2019) estimate the adoption elasticity parameter $1-\varphi$ to be about 0.925, so a prior mean of 0.075 is chosen for φ. Finally, the capital share α is usually set to $\frac{1}{3}$ in the literature so the prior mean for α is set to this value. Table 2.2 summarizes the assumptions on the parameter prior distributions. Table 2.3 then summarizes

Table 2.2: Assumptions on Prior distributions

Parameter	Type	Mean	Std. Error
ξ	BETA	0.567	0.025
κ	BETA	0.3	0.025
α	BETA	$\frac{1}{3}$	0.025
φ	BETA	0.075	0.025
τ	BETA	0.204	0.025
ρ^f	BETA	0.85	0.05
ρ^q	BETA	0.85	0.05
ρ^j	BETA	0.85	0.05
ρ^g	BETA	0.286	0.05
s.e. ε^f	INV. GAMMA	0.07	2
s.e. ε^q	INV. GAMMA	0.01	2
s.e. ε^j	INV. GAMMA	0.08	2
s.e. ε^g	INV. GAMMA	0.35	2
s.e. ι^{xy}	INV. GAMMA	0.01	2

the estimation results for the posterior distributions[10]. Finally, figure 2.4 plots the prior and posterior densities for the estimated model parameters, while figure 2.5 plots the prior and posterior densities for the estimated shock standard errors. All of the parameter modes estimated above take reasonable values comparable to the literature, thus the model above seems to be in line with the major findings of the related literature concerning the estimated parameters. Only the mode for the parameter α is a little bit lower than usually assumed, but with a narrow posterior distribution around it and not out of the reasonable range.

2.4.2 How labor market fluctuations affect long-run technological progress

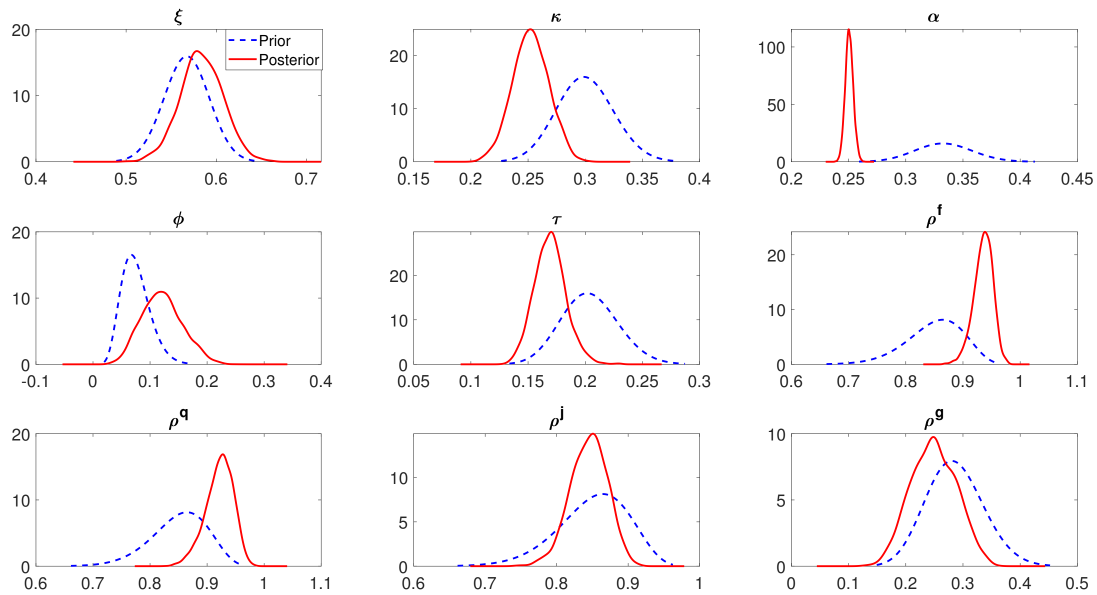
Now the estimated model is used to assess the question to what extent the shift of the Beveridge Curve during the Great Recession affected endogenous long-run

[10]Posterior distributions received by employing the Metropolis Hastings algorithm. The algorithm uses a Markov-Chain-Monte-Carlo (MCMC) simulation with 20,000 draws in total, while 10,000 draws are finally kept and another 10,000 draws discarded as burning-in draws.

Table 2.3: Properties of the posterior distributions

Parameter	Mode	Std. Error (Hessian)	5%	Mean	95%
ξ	0.5825	0.0217	0.5465	0.5835	0.6243
κ	0.2528	0.0129	0.2269	0.2521	0.2789
α	0.2506	0.0032	0.2450	0.2505	0.2566
φ	0.1095	0.0310	0.0658	0.1209	0.1825
τ	0.1688	0.0125	0.1462	0.1691	0.1916
ρ^f	0.9385	0.0158	0.9098	0.9352	0.9630
ρ^q	0.9288	0.0190	0.8808	0.9212	0.9586
ρ^j	0.8451	0.0254	0.8014	0.8446	0.8853
ρ^g	0.2442	0.0317	0.1851	0.2484	0.3135
s.e. ε^f	0.0668	0.0067	0.0579	0.0684	0.0788
s.e. ε^q	0.0096	0.0008	0.0084	0.0098	0.0112
s.e. ε^j	0.0801	0.0074	0.0700	0.0818	0.0924
s.e. ε^g	0.3365	0.0306	0.2976	0.3433	0.3872
s.e. ι^{xy}	0.0026	0.0002	0.0022	0.0026	0.0030

Figure 2.4: Prior and posterior densities for the estimated model parameters.



technological progress. At first, figure 2.6 shows the impulse responses of the TFP level q_t (retrieved by integrating over the effect on the TFP growth rate g_t^q), the value of being the incumbent $\mathcal{M}_t$, the job filling probability Φ_t^v, the stock of unadopted ideas U_t, production of new ideas R_t and adoption effort Υ_t to a matching efficiency shock of size one standard deviation, which translates to an increase in matching efficiency of about 7%. As it can be seen, a matching efficiency shock of

Figure 2.5: Prior and posterior densities for the estimated shock standard errors.

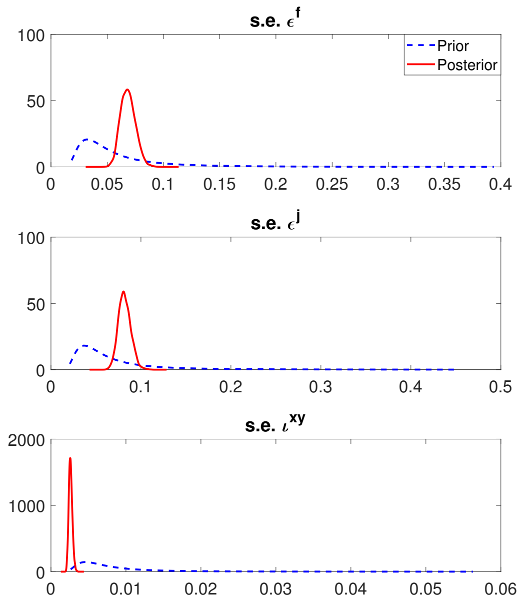
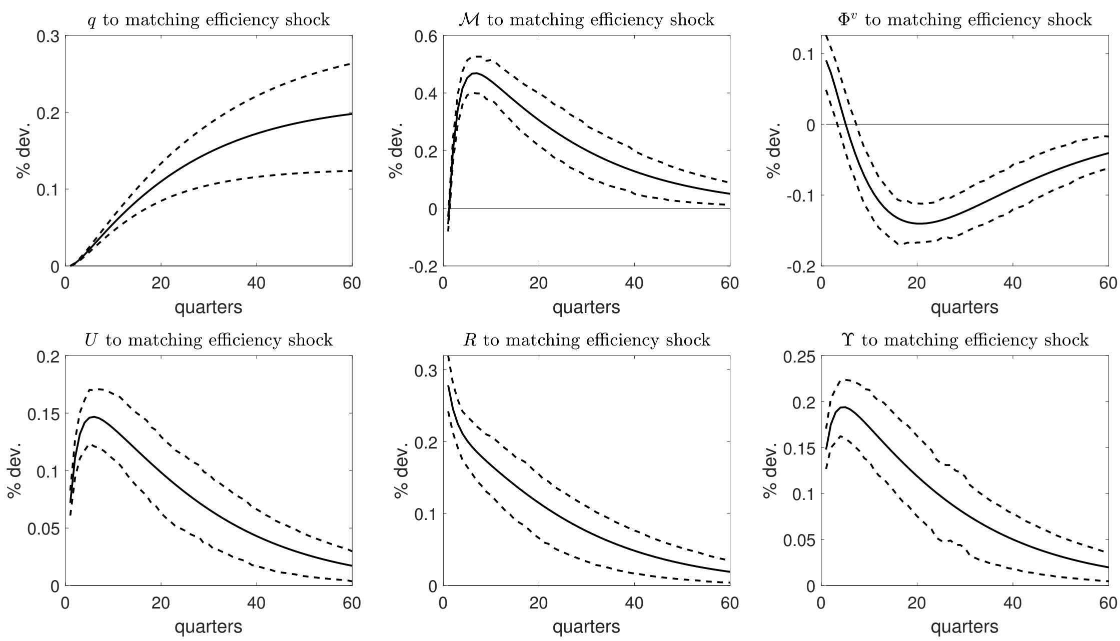


Figure 2.6: Impulse responses of TFP and variables associated with endogenous TFP growth to a 1 standard deviation shock in matching efficiency (increase in matching efficiency about 7%) as implied by the estimated model. The dashed lines give the 90% credible interval based on the highest posterior density interval (HPDI).

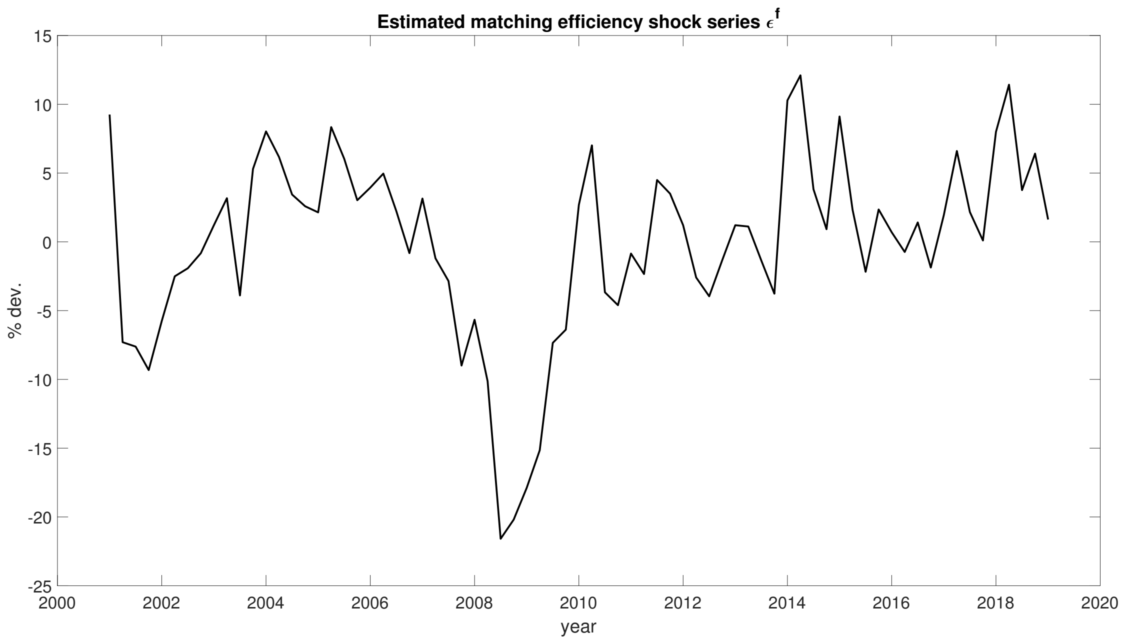


about one standard deviation leads to a long-run increase in the TFP level q until it settles down to a nearly 0.2% higher TFP than without the shock after about 60 quarters. The reasoning for this long-run increase is as follows: On impact of the matching efficiency shock, the job filling probability Φ^v increases by about 0.1%, thus the labor hiring costs decrease and the entrance barrier for outside firms is lowered. Consequently, the competitive pressure in the innovation race increases and firms will demand more new technologies, which leads to an increase in technology adoption effort Υ about 0.15%, an increase in research spending R of nearly 0.3% and thus an increase in the stock of unadopted technologies U of about 0.075%. The higher matching efficiency on the labor market leads to a medium-run decrease in the number of unemployed (for a further discussion of the business cycle effects of the matching efficiency shock see the appendix), thus with a declining shock effect and an increase in the labor market tightness $\theta_t = \frac{v_t}{u_t}$, the effect on the job filling probability becomes negative after about 10 quarters and decreases by over 0.1% after 20 quarters, thus hiring cost increase again. However, on the other side the higher existing stock of workers of the incumbents implies lesser overall need for hiring and thus lesser future hiring costs. Consequently, the value of being the incumbent $\mathcal{M}$ increases, in fact about nearly 0.5% after 10 quarters, and thus the incentive for innovation remains above the steady state and declines only slowly over 60 quarters, so the above average growth in TFP continues over this period of time.

So what can be seen is that the size of the reaction of endogenous TFP to the matching efficiency shock is relatively small in the short run and it needs time until the effect becomes more sizable. This is because the technology adoption and innovation effort might decrease immediately, but due to the process of technology adoption, the long-run effect only kicks in over time. So a one standard deviation shock to matching efficiency does not incur much fluctuation in the endogenous TFP growth rate in the short run, but unfolds in the medium run. Consequently, if one wants to have a look on the effect of the outward shift of the Beveridge Curve on endogenous TFP during the Great Recession, one has to look at the longer-run implications.

Furthermore, one has to keep in mind that the strong decrease in matching efficiency during the Great Recession is unprecedented for the data sample at hand. Figure 2.7 shows the smoothed matching efficiency shock series estimated using the Kalman-filter from the model. The outward shift in the Beveridge Curve is visible in the large negative shock to the matching efficiency between 2008 and 2010, where

Figure 2.7: Historical simulation of the identified matching efficiency shock series as implied by the model



matching efficiency dropped by over 20%. The negative matching efficiency shock during the Great Recession identified by the model matches the findings of Barlevy (2011) and Sedláček (2014) in timing and size, suggesting that the estimated model performs well in mimicking the events during the Great Recession. As it can be seen, the sharp decline in matching efficiency during the Great Recession is strong compared to its usual fluctuations. Consequently, also the effect of the matching efficiency shock during the Great Recession is stronger than usual, because the shocks itself were exceptionally large during this time, in fact so strong that the Beveridge Curve shifted outwards visibly.

To assess the overall importance of matching efficiency shocks for technological progress, a variance decomposition is performed. Define $g^{qt} = \ln(\lambda)\Delta^A$, the trend component of TFP growth, table 2.4 then shows the variance decomposition in percent for the endogenous TFP growth rate, cyclical output $\tilde{Y}$, unemployment u and vacancies v. As becomes evident, overall the matching efficiency shock ε^f is not responsible for most of the overall variance in the endogenous TFP growth rate, as it only explains about nearly 9% of it. The most dominant contributor to the variance in the endogenous TFP growth rate is the consumer preference shock ε^g, which explains over 88% of it, while the influence of TFP and job destruction shocks is negligible. Demand side shocks being decisive for endogenous TFP growth in the

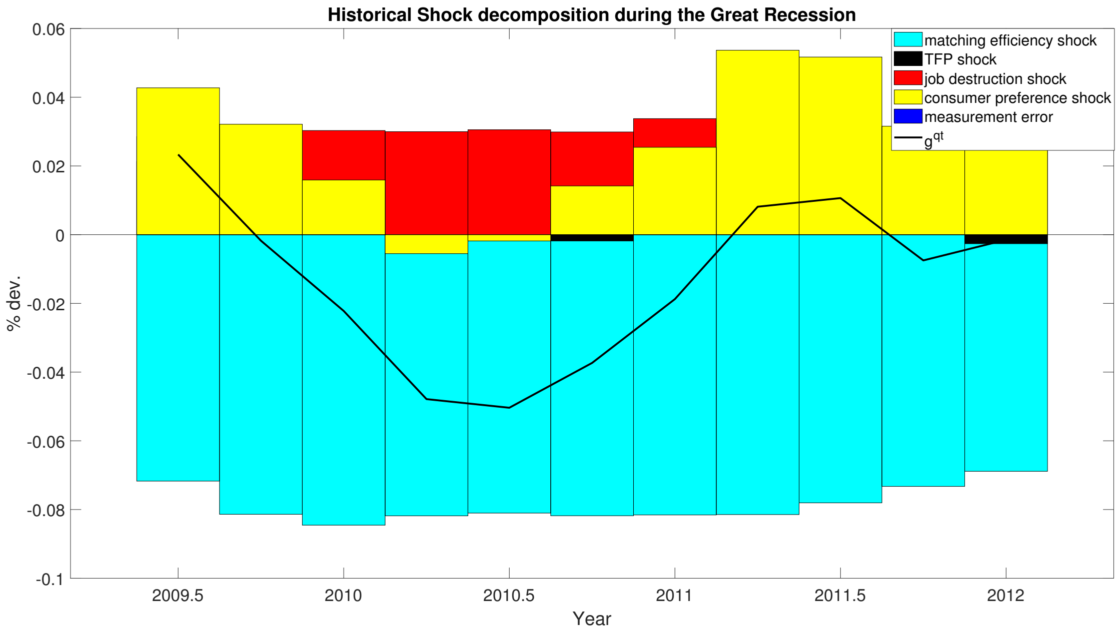
Table 2.4: Variance Decomposition (in Percent)

Variable	ε^f	ε^q	ε^j	ε^g
g^{qt}	8.70	1.22	1.65	88.44
u	79.30	0.04	18.41	2.25
v	28.55	0.76	40.04	30.65
$\tilde{Y}$	9.97	16.23	2.12	71.68

model above is, however, not surprising, as higher demand allows for higher profits of the intermediate firms and thus a higher incentive to stay in or get into the market with more innovations. Furthermore, in the appendix it is shown that the business cycle itself is mostly demand-driven, thus as short-run shocks induce medium-run fluctuations due to technology adoption, it is unsurprising that demand shocks are also to a large extent responsible for fluctuations in technological progress. Looking at the labor market, obviously the labor market related shocks explain most of the variation in unemployment and vacancies, where matching efficiency shocks are very influential for the variance of unemployment, explaining nearly 80% of it, while job destruction shocks ε^j are the most influential factor for the variation in vacancies, explaining about 40% of it. From the variance decomposition of cyclical output, it becomes evident that matching efficiency shocks play an inferior role here, as most of the variance in cyclical output is driven by the consumer preference shock and the TFP shock.

The variance decomposition yields the unsurprising insight that the variance of labor market variables is mostly influenced by labor market related shocks, while cyclical output and endogenous TFP growth fluctuations are mostly influenced by the demand side shock. However, figure 2.8 takes a closer look on the time between 2008 and 2012, showing the influence of the 4 structural shocks during the Great Recession. The solid line shows the historical simulation for the percentage point deviation of endogenous TFP growth from its steady state during the Great Recession, the teal bars depict the influence of matching efficiency shocks, the yellow bars the influence of consumer preference shocks and the red bars the impact of job destruction shocks. The impact of TFP shocks (black bars) and the measurement error (blue bars) is negligible. As becomes evident, despite being not a main contributor to the overall variance of the endogenous TFP growth rate, the shock decomposition shows that during the Great Recession the decline in matching efficiency was the main reason for the decline in endogenous TFP growth. So while not being very influential during normal times, the outward shift of the Beveridge Curve due to a sharp decline in matching efficiency was a main contributor for

Figure 2.8: Shock decomposition for endogenous TFP growth during the Great Recession



the slowdown in endogenous TFP growth during the Great Recession. Performing a counterfactual analysis, so calculating what TFP could have been without the drop in matching efficiency, it turns out that in 2019 TFP is about 0.6% lower than without the shock. Judging by the impulse responses in figure 2.6, where the new long-run level is approximately reached after 60 quarters, one can expect the full effect of the outward shift of the Beveridge Curve to fully materialize at least in a few years from now on, thus the full long-run loss in TFP due to the negative matching efficiency shock during the Great Recession is likely to be stronger.

2.5 Conclusion

The present paper reasons that the observed outward shift in the Beveridge Curve during the Great Recession between 2008 and 2012 caused a slowdown in endogenous TFP growth. It proposes a model, where search frictions in the labor market impose an additional entry barrier to outside firms, who do not have any worker stock yet and thus are structurally disadvantaged against incumbent firms in the market. If the matching efficiency decreases and thus the Beveridge Curve shifts out, the probability of filling a vacancy for firms decreases and it becomes more costly for outsiders to hire a stock of workers. Firms are in Schumpeterian competition for the spot as market incumbent, in consequence the additional labor hiring costs for outside firms leave them less resources for innovation to attain a higher quality than incumbents and replace them. The reduced innovative pressure on the incumbents then gives them an incentive to reduce innovation spending as well and overall technological progress decreases.

Estimating the model, it turns out that matching efficiency shocks are not an important contributor to the variance of endogenous TFP growth during normal times, but were a major reason for the decline in endogenous TFP growth during the Great Recession. The reason why the effect was so strong during the Great Recession is that the matching efficiency shock during the Great Recession was exceptionally strong during this time, where matching efficiency dropped by over 20%. Comparing the TFP level in 2019 with its counterfactual without the strong negative matching efficiency shock during the Great Recession, it turns out that the loss has amassed to over 0.6%. The finding of permanent TFP losses due to negative matching efficiency shocks gives rise to the possibility that labor market policy has not only short-run, but also long-run consequences, as the economy can benefit in the long run, if strong structural mismatches on the labor market like during the Great Recession can be avoided. It thus cannot only avoid undesirable short-run unemployment, but also yield long-run productivity gains. With the gain of labor market policies being higher than anticipated by standard models, optimal labor market policy is likely to be more aggressive against structural mismatches than models excluding endogenous technological progress would predict. An interesting avenue for future research thus would be to study optimal labor market policy in a model including endogenous technological progress.

2.6 Appendix: Further derivations for section 2.3

2.6.1 Detrended form of the model

In order to perform a linear approximation around the steady state for the model, it has to be detrended. Notice that $q_t = \lambda^{A_{t-1}} exp(e_t)$. So the TFP level is driven by a growing trend component $q_{t-1}^t = \lambda^{A_{t-1}}$ and a stationary business cycle component $q_t^c = exp(e_t)$. On the balanced growth path, all growing variables grow at the rate of the trend TFP growth rate. To eliminate the trend, every growing variable has to be divided by q_{t-1}^t, which yields a stationary model in detrended form. Variables growing on the balanced growth path are: the real wage w_t, the marginal revenue product of labor Θ_t, unemployment benefits b_t, R&D spending X_t, the price for new unadopted goods p_t^R, the license price $p_t^{\mathcal{U}}$, adoption effort Υ_t, the price for adopted technologies p_t^A, aggregate output Y_t, intermediate good output z_t, physical capital K_t, vacancy posting costs ς_t, expected lifetime firm profits $\mathcal{M}_t$, consumption C_t and investment I_t. All other variables are stationary on the balanced growth path. Detrended variables are denoted by a tilde, so the detrended form model equations read (where $g_t^{qt} = \frac{q_{i,t}^t - q_{i,t-1}^t}{q_{i,t-1}^t}$):

$$\Phi^v(\theta_t) = \mu_t \left(\frac{1}{\theta_t}\right)^{\xi} \tag{2.85}$$

$$\theta_t = \frac{v_t}{u_t} \tag{2.86}$$

$$\mu_t = \bar{\mu}\exp(f_t) \tag{2.87}$$

$$f_t = \rho^f f_{t-1} + \varepsilon_t^f \tag{2.88}$$

$$\tilde{w}_t = \tau\tilde{\Theta}_t + (1-\tau)\tilde{b}_t \tag{2.89}$$

$$\tilde{\Theta}_t = p_t^z exp(e_t) \tag{2.90}$$

$$\tilde{b}_t = (1-\omega)\tilde{w}_t \tag{2.91}$$

$$R_t = \chi\left(\frac{\tilde{X}_t}{exp(e_t)}\right)^{1-\kappa} \tag{2.92}$$

$$(1-\kappa)\chi\frac{\tilde{p^R}_t}{exp(e_t)} = \left(\frac{\tilde{X}_t}{\exp(e_t)}\right)^{\kappa} \tag{2.93}$$

$$\mathcal{U}_t = (1-\delta^{\mathcal{U}})\mathcal{U}_{t-1} + R_t - \Delta_t^A \tag{2.94}$$

$$\tilde{p^R}_t = E_t\Lambda_{t,t+1}\tilde{p^{\mathcal{U}}}_{t+1}(1+g_t^{qt}) \tag{2.95}$$

$$\Lambda_{t,t+1} = E_t\frac{1}{1+r_{t+1}^K-\delta^K} \tag{2.96}$$

$$\Delta_t^A = \gamma\left(\frac{\tilde{\Upsilon}_t}{exp(e_t)}\right)^{1-\varphi}\mathcal{U}_{t-1} \tag{2.97}$$

$$\frac{\tilde{p^A}_t}{exp(e_t)}(1-\varphi)\gamma\mathcal{U}_{t-1} = \left(\frac{\tilde{\Upsilon}_t}{exp(e_t)}\right)^{\varphi} \tag{2.98}$$

$$\tilde{p^A}_t\gamma\left(\frac{\tilde{\Upsilon}_t}{exp(e_t)}\right)^{1-\varphi} = \tilde{p^{\mathcal{U}}}_t \tag{2.99}$$

$$\tilde{Y}_t = \frac{1}{1-\alpha}\tilde{z}_t^{1-\alpha}\tilde{K}_{t-1}^{\alpha} \tag{2.100}$$

$$\tilde{z}_t = (p_t^z)^{-\frac{1}{\alpha}}\tilde{K}_{t-1} \tag{2.101}$$

$$r_t^K = \frac{\alpha}{1-\alpha}\tilde{z}_t^{1-\alpha}\tilde{K}_{t-1}^{\alpha-1} \tag{2.102}$$

$$\tilde{z}_t = exp(e_t)n_t \tag{2.103}$$

$$e_t = \rho^q e_{t-1} + \varepsilon_t^q \tag{2.104}$$

$$\frac{\tilde{\varsigma}_t}{exp(e_t)} = \bar{\varsigma} \tag{2.105}$$

$$\delta_t^j = \bar{\delta}^j exp(d_t) \tag{2.106}$$

$$d_t = \rho^j d_{t-1} + \varepsilon_t^j \tag{2.107}$$

$$n_t = (1-\delta_t^j)n_{t-1} + \Phi^v(\theta_t)v_t \tag{2.108}$$

$$p_t^z = \frac{1}{1-\alpha}\left[\frac{\tilde{w}_t}{exp(e_t)} + \frac{\bar{\varsigma}}{\Phi^v(\theta_t)} - E_t\Lambda_{t,t+1}(1-\delta_{t+1}^j)\frac{\bar{\varsigma}}{\Phi^v(\theta_{t+1})}(1+g_{t+1}^q)\right] \tag{2.109}$$

$$g_t^{qt} = \frac{q_{i,t}^t - q_{i,t-1}^t}{q_{i,t-1}^t} \approx \ln(\lambda)\Delta_t^A \tag{2.110}$$

$$\Delta_t^A = \frac{E_t\Lambda_{t,t+1}(1+g_t^{qt})\left(\tilde{\mathcal{M}}_t - \bar{\varsigma}exp(e_t)\frac{(1-\delta_{t+1}^j)n_t}{\Phi^v(\theta_{t+1})}\right)}{\tilde{p^A}_t} \tag{2.111}$$

$$\tilde{\mathcal{M}}_t = p_t^z\tilde{z}_t - \tilde{w}_t n_t - \bar{\varsigma}exp(e_t)v_t - \tilde{p^A}_t\Delta_t^A + E_t\Lambda_{t,t+1}\tilde{\mathcal{M}}_{t+1}(1+g_t^{qt}) \tag{2.112}$$

$$\tilde{K}_t(1+g_t^{qt}) = (1-\delta^K)\tilde{K}_{t-1} + \tilde{I}_t \tag{2.113}$$

$$u_t + n_t = 1 \tag{2.114}$$

$$\tilde{C}_t^{-1} = E_t\beta\frac{exp(g_{t+1})}{exp(g_t)}\frac{1+r_{t+1}^K-\delta^K}{1+g_t^{qt}}\tilde{C}_{t+1}^{-1} \tag{2.115}$$

$$g_t = \rho^g g_{t-1} + \varepsilon_t^g \tag{2.116}$$

$$\tilde{Y}_t = \tilde{C}_t + \tilde{I}_t \tag{2.117}$$

The detrended model above then can be approximated linearly using Dynare. The next section derives the steady state of the model and discusses its stability and uniqueness.

2.6.2 Steady state of the detrended form model

For the detrended form model derived in the previous section there exists a steady state determined by the following conditions (asterisks denote steady state values), calculated by dropping time indices:

$$\Phi^v(\theta^*) = \mu^*\left(\frac{1}{\theta^*}\right)^\xi \tag{2.118}$$

$$\theta^* = \frac{v^*}{u^*} \tag{2.119}$$

$$\mu^* = \bar{\mu} \tag{2.120}$$

$$f^* = 0 \tag{2.121}$$

$$\tilde{w}^* = \tau\tilde{\Theta}^* + (1-\tau)\tilde{b}^* \tag{2.122}$$

$$\tilde{\Theta}^* = p^{z*} \tag{2.123}$$

$$\tilde{b}^* = (1-\omega)\tilde{w}^* \tag{2.124}$$

$$R^* = \chi\left(\tilde{X}^*\right)^{1-\kappa} \tag{2.125}$$

$$(1-\kappa)\chi p^{\tilde{R}*} = \left(\tilde{X}^*\right)^{\kappa} \tag{2.126}$$

$$\mathcal{U}^* = \frac{R^* - \Delta^{A*}}{\delta^{\mathcal{U}}} \tag{2.127}$$

$$p^{\tilde{R}*} = \Lambda^* p^{\tilde{\mathcal{U}}*}(1+g^{qt*}) \tag{2.128}$$

$$\Lambda^* = \frac{1}{1+r^{K*}-\delta^K} \tag{2.129}$$

$$\Delta^{A*} = \gamma\left(\tilde{\Upsilon}^*\right)^{1-\varphi}\mathcal{U}^* \tag{2.130}$$

$$p^{\tilde{A}*}(1-\varphi)\gamma\mathcal{U}^* = \left(\tilde{\Upsilon}^*\right)^{\varphi} \tag{2.131}$$

$$p^{\tilde{A}*}\gamma\left(\Upsilon^*\right)^{1-\varphi} = p^{\tilde{\mathcal{U}}*} \tag{2.132}$$

$$\tilde{Y}^* = \frac{1}{1-\alpha}(\tilde{z}^*)^{1-\alpha}(\tilde{K}^*)^{\alpha} \tag{2.133}$$

$$\tilde{z}^* = (p^{z*})^{-\frac{1}{\alpha}}\tilde{K}^* \tag{2.134}$$

$$r^{K*} = \frac{\alpha}{1-\alpha}(\tilde{z}^*)^{1-\alpha}(\tilde{K}^*)^{\alpha-1} \tag{2.135}$$

$$\tilde{z}^* = n^* \tag{2.136}$$

$$e^* = 0 \tag{2.137}$$

$$\varsigma^* = \bar{\varsigma} \tag{2.138}$$

$$\delta^{j*} = \bar{\delta}^j \tag{2.139}$$

$$d^* = 0 \tag{2.140}$$

$$n^* = \frac{\Phi^v(\theta^*)v^*}{\delta^{j*}} \tag{2.141}$$

$$p^{z*} = \frac{1}{1-\alpha}\left[\tilde{w}^* + \frac{\bar{\varsigma}}{\Phi^v(\theta^*)} - \Lambda^*(1-\delta^{j*})\frac{\bar{\varsigma}}{\Phi^v(\theta^*)}(1+g^{qt*})\right] \tag{2.142}$$

$$g^{qt*} \approx \ln(\lambda)\Delta^{A*} \tag{2.143}$$

$$\Delta^{A*} = \frac{\Lambda^*(1+g^{qt*})\left(\tilde{\mathcal{M}}^* - \bar{\varsigma}\frac{(1-\delta^{j*})n^*}{\Phi^v(\theta^*)}\right)}{p^{\tilde{A}*}} \tag{2.144}$$

$$\tilde{\mathcal{M}}^* = p^{z*}\tilde{z}^* - \tilde{w}^* n^* - \bar{\varsigma}v^* - p^{\tilde{A}*}\Delta^{A*} + \Lambda^*(1+g^{qt*})\tilde{\mathcal{M}}^* \tag{2.145}$$

$$\tilde{I}^* = (g^{qt*}+\delta^K)\tilde{K}^* \tag{2.146}$$

$$n^* = 1-u^* \tag{2.147}$$

$$\beta = \frac{1 + g^{qt*}}{1 + r^{K*} - \delta^K} \tag{2.148}$$

$$g^* = 0 \tag{2.149}$$

$$\tilde{Y}^* = \tilde{C}^* + \tilde{I}^* \tag{2.150}$$

There are 9 forward looking variables and 9 eigenvalues larger than 1 in modulus, so the Blanchard-Kahn conditions are fulfilled and a unique and stable steady state for the detrended model exists. The detrended model can thus be analyzed using standard perturbation methods and the Dynare software. The long-run implications can be retrieved by integrating over the TFP growth rate.

2.6.3 Recalculation of TFP growth in contrast to Fernald (2012-2019)

The TFP growth series calculated by Fernald (2012-2019) is defined as the residual between output and input growth. He assumes a production function with capital and labor augmenting technological progress of the form (variable definitions as before)

$$Y_t = q_t^{Fernald} K_{t-1}^{\alpha} n_t^{1-\alpha} \tag{2.151}$$

and by taking logs and first differences

$$\begin{aligned} &\ln(Y_t) - \ln(Y_{t-1}) = \alpha \left(\ln(K_{t-1}) - \ln(K_{t-2})\right) + (1-\alpha)\left(\ln(n_t) - \ln(n_{t-1})\right) + g_t^{q,Fernald} \\ \Leftrightarrow\ & g_t^{q,Fernald} = \ln(Y_t) - \ln(Y_{t-1}) - \alpha \left(\ln(K_{t-1}) - \ln(K_{t-2})\right) - (1-\alpha)\left(\ln(n_t) - \ln(n_{t-1})\right). \end{aligned} \tag{2.152}$$

However, the model in this paper assumes purely labor augmenting technological progress, so the production function reads

$$Y_t = \frac{1}{1-\alpha} K_{t-1}^{\alpha} \left(q_t n_t\right)^{1-\alpha}, \tag{2.153}$$

thus by taking logs and first differences

$$\begin{aligned} &\ln(Y_t) - \ln(Y_{t-1}) = \alpha \left(\ln(K_{t-1}) - \ln(K_{t-2})\right) + (1-\alpha)\left(\ln(n_t) - \ln(n_{t-1}) + g_t^q\right) \\ \Leftrightarrow\ & (1-\alpha) g_t^q = \ln(Y_t) - \ln(Y_{t-1}) - \alpha \left(\ln(K_{t-1}) - \ln(K_{t-2})\right) - (1-\alpha)\left(\ln(n_t) - \ln(n_{t-1})\right) \end{aligned} \tag{2.154}$$

and thus

$$g_t^q = \frac{1}{1-\alpha} g_t^{q,Fernald}. \tag{2.155}$$

In order to make the observed TFP series fitting to the model implied TFP series, the data series of Fernald (2012-2019) is multiplied with $\frac{1}{1-\alpha}$. In fact Fernald (2012-2019) also provides data on the capital share α_t for each observation period, which is used to recalculate the TFP series before estimating the parameter α from the model, which is assumed to be constant and not time-varying. The recalculation of the TFP growth rate does not have strong implications for the estimated parameters, shocks and impulse responses, but mainly affects the scaling parameters. In consequence, the main implications of the paper are unaffected by the changes in the TFP growth calculation.

2.7 Appendix: Computational details

In order to make the computation more robust and less dependent on initial values for numerical solver routines, the steady state system of equations can be reduced to two equations in the two unknowns u^* and $\tilde{\Upsilon}^*$. The two steady state conditions then read

$$\tilde{\Upsilon}^* - \beta(1-\varphi)\left[\tilde{\mathcal{M}}^* - \frac{\varsigma(1-\bar{\delta}^j)(1-u^*)}{\bar{\mu}\left(\frac{u^*}{v^*}\right)^{\xi}}\right] \stackrel{!}{=} 0 \tag{2.156}$$

$$\left(\frac{1+\ln(\lambda)\gamma(\tilde{\Upsilon}^*)^{1-\varphi}\mathcal{U}^*}{\beta} - 1 + \delta^K\right) - \left(\frac{\alpha}{1-\alpha}(1-u^*)^{1-\alpha}(\tilde{K}^*)^{\alpha-1}\right) \stackrel{!}{=} 0, \tag{2.157}$$

with

$$v^* = \left(\frac{\bar{\delta}^j(1-u^*)}{\bar{\mu}(u^*)^{\xi}}\right)^{\frac{1}{1-\xi}} \tag{2.158}$$

$$p^{z*} = \left(\frac{1-\beta(1-\bar{\delta}^j)}{1-\alpha}\right)\frac{1}{1-\left(\frac{\tau}{(1-\alpha)(1-(1-\tau)(1-\omega))}\right)}\frac{\varsigma}{\bar{\mu}\left(\frac{u^*}{v^*}\right)^{\xi}} \tag{2.159}$$

$$\tilde{K}^* = (1-u^*)(p^{z*})^{\frac{1}{\alpha}} \tag{2.160}$$

$$\mathcal{U}^* = \left(1+\frac{\gamma}{\delta^{\mathcal{U}}}(\tilde{\Upsilon}^*)^{1-\varphi}\right)^{-\kappa}\left(\frac{\chi}{\delta^{\mathcal{U}}}\right)^{\kappa}\left(\frac{(1-\kappa)\chi\beta\tilde{\Upsilon}^*}{1-\varphi}\right)^{1-\kappa} \tag{2.161}$$

$$\mathcal{M}^* = \frac{1}{1-\beta}\left[\left(1-\left(\frac{\tau}{1-(1-\tau)(1-\omega)}\right)\right)p^{z*}(1-u^*) - \varsigma v^* - \frac{\tilde{\Upsilon}^*}{1-\varphi}\right]. \tag{2.162}$$

This system of equations can then be solved using the fsolve routine of Matlab, which uses a trust-region dogleg algorithm, a variant of the Powell dogleg method, by default to find a numerical solution for u^* and $\tilde{\Upsilon}^*$. The remaining variables that are non-zero or given by a parameter are then found by reinserting u^*, $\tilde{\Upsilon}^*$, v^*, p^{z*}, $\tilde{K}^*$, $\mathcal{U}^*$ and $\mathcal{M}^*$ in the following equations

$$\Phi^{v*} = \bar{\mu}\left(\frac{u^*}{v^*}\right)^{\xi} \tag{2.163}$$

$$\theta^* = \frac{v^*}{u^*} \tag{2.164}$$

$$\tilde{w}^* = \frac{\tau}{1-(1-\tau)(1-\omega)}p^{z*} \tag{2.165}$$

$$\tilde{\Theta}^* = p^{z*} \tag{2.166}$$

$$\tilde{b}^* = (1-\omega)\tilde{w}^* \tag{2.167}$$

$$p^{\tilde{\mathcal{U}}*} = \frac{\tilde{\Upsilon}^*}{(1-\varphi)\mathcal{U}^*} \tag{2.168}$$

$$\tilde{X}^* = \left[(1-\kappa)\chi\beta p^{\tilde{\mathcal{U}}*}\right]^{\frac{1}{\kappa}} \tag{2.169}$$

$$R^* = \chi(\tilde{X}^*)^{1-\kappa} \tag{2.170}$$

$$p^{\tilde{R}*} = \beta p^{\tilde{\mathcal{U}}*} \tag{2.171}$$

$$r^{K*} = \frac{\alpha}{1-\alpha}(1-u^*)^{1-\alpha}(\tilde{K}^*)^{\alpha-1} \tag{2.172}$$

$$\Lambda^* = \frac{1}{1+r^{K*}-\delta^K} \tag{2.173}$$

$$\Delta^{A*} = \gamma(\tilde{\Upsilon}^*)^{1-\varphi}\mathcal{U}^* \tag{2.174}$$

$$p^{\tilde{A}*} = \frac{p^{\tilde{\mathcal{U}}*}}{\gamma(\tilde{\Upsilon}^*)^{1-\varphi}} \tag{2.175}$$

$$\tilde{Y}^* = \frac{1}{1-\alpha}(1-u^*)^{1-\alpha}(\tilde{K}^*)^{\alpha} \tag{2.176}$$

$$\tilde{z}^* = 1-u^* \tag{2.177}$$

$$n^* = \tilde{z}^* \tag{2.178}$$

$$g^{qt*} = \ln(\lambda)\Delta^{A*} \tag{2.179}$$

$$\tilde{I}^* = (g^{qt*}+\delta^K)\tilde{K}^* \tag{2.180}$$

$$\tilde{C}^* = \tilde{Y}^* - \tilde{I}^*. \tag{2.181}$$

These results are passed on to the Dynare steady state file. For the Bayesian estimation, the Monte-Carlo based optimization routine (mode_compute = 6 in Adjemian et al. (2011)) is used.

2.8 Appendix: Business cycle effects of the matching efficiency shock

The main body of this paper investigates the long-run consequences of matching efficiency shocks that are so far not considered by the related literature. In order to check on the plausibility of the model implications regarding the identified matching efficiency shock, its short-run business cycle effects on variables like output, consumption, investment, wages, unemployment and vacancies are discussed. As a first step, table 2.5 summarizes the variance decomposition for these variables regarding the four structural shocks considered in the model. As it becomes evi-

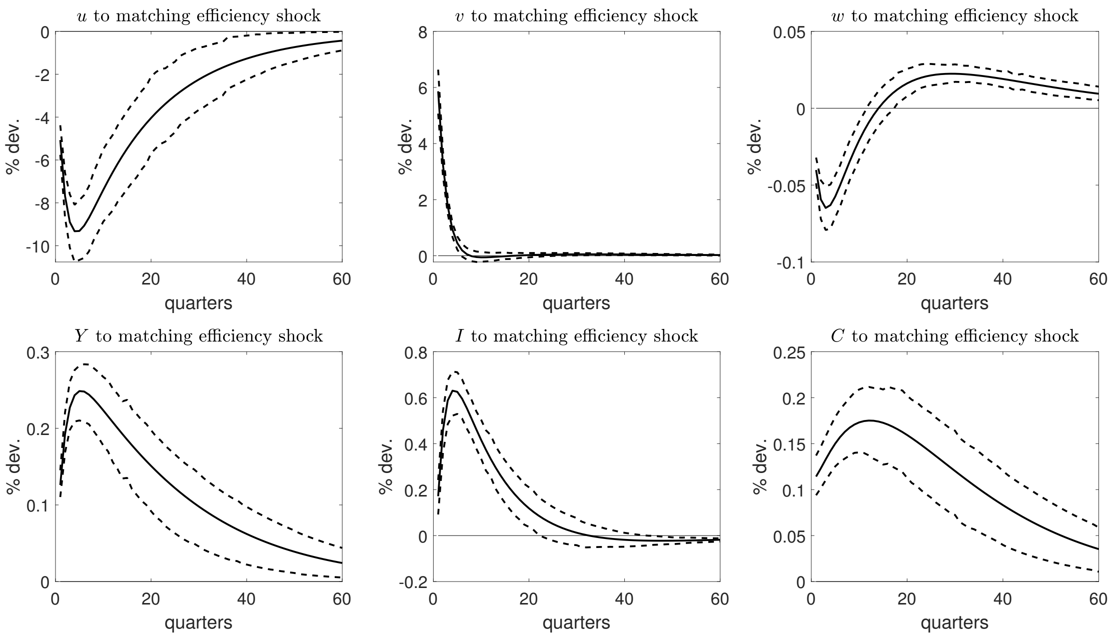
Table 2.5: Variance Decomposition (in Percent)

Variable	ε^f	ε^q	ε^j	ε^g
u	79.30	0.04	18.41	2.25
v	28.55	0.76	40.04	30.65
$\tilde{w}$	0.51	20.87	0.17	78.44
$\tilde{Y}$	9.97	16.23	2.12	71.68
$\tilde{I}$	0.06	0.15	0.03	99.76
$\tilde{C}$	0.22	0.33	0.04	99.42

dent, the matching efficiency shock is overall not responsible for the major part of the variance in real wages, output, consumption and investment. In fact, business cycle fluctuations of these variables seem to be demand driven, as the consumer preference shock is able to explain the variance in consumption and investment almost on its own and, together with the TFP shock, the bulk of the variance in output and real wages. Unsurprisingly however, matching efficiency shocks have a much stronger effect on vacancies and unemployment. Regarding vacancies, the matching efficiency shock explains like consumer preference shocks about 30% of the variance, falling behind job destruction shocks that explain about 40%. For the unemployment rate, matching efficiency shocks explain about 80% of the variance, while the influence of TFP and consumer preference shocks seems to be negligible. Summing up and in line with a common view of the business cycle, fluctuations in output, wages, investment and consumption are mainly demand-driven (see Beaudry and Portier (2014) for a discussion), while matching efficiency shocks are mainly influential concerning labor market variables like unemployment and firm vacancies.

In the analysis of business cycle effects, it is common to evaluate the impulse responses of the detrended, "cyclical" part of variables like output, investment, real wages or consumption, where the term "cyclical" refers to high frequency fluctuations. The relevant counterparts from the detrended model are $\tilde{Y}$, $\tilde{I}$, $\tilde{W}$ and $\tilde{C}$. Figure 2.9 shows the impulse responses of these variables, unemployment rate and vacancy rate to a matching efficiency shock of size one standard-deviation. In con-

Figure 2.9: Impulse responses of unemployment, vacancies, detrended wages, detrended output, detrended investment and detrended consumption to a 1 standard deviation shock in matching efficiency as implied by the estimated model. The dashed lines give the 90% credible interval based on the highest posterior density interval (HPDI).



sequence of a matching efficiency shock, the unemployment rate decreases about 4% on impact and about 9% within the first 5 quarters. After that, the unemployment rate slowly returns back to its mean. Higher matching efficiency means that the probability of finding a job for an unemployed increases, thus aggregate unemployment decreases. After the shock effect on the job finding probability gets weaker, the exogenous job destruction gets stronger than the additional job creation and unemployment slowly returns back to its steady state level. The exogenously higher matching efficiency also increases the job filling probability for the firms and thus reduces their hiring costs. Consequently, vacancies increase by about 6% on impact, but return back to their steady state within 10 quarters as the shock effect on the job filling probability declines again. Regarding wages, the decline in hiring cost in consequence of the matching efficiency shock implies a decrease in the price markup for intermediate goods on impact and thus a lower marginal revenue product of labor, which implies a decline of the real wage of about 0.05%. As the job filling probability begins to decline again and hiring costs increase, the price markup and marginal revenue product increase, so wages start to increase again. As the economy is growing faster in the medium run, the stochastic discounting factor $\Lambda_{t,t+1}$ decreases and the expected future value of existing jobs decreases. Firms will compensate the loss in job value with a higher intermediate goods price, thus the marginal revenue product of labor and wages overshoot the steady state, before slowly returning back to it again. On the other side, the decrease in unemployment leads to an increase in household income and demand, thus output and consumption increase about 0.2% on impact and slowly return back to the steady state over more than 40 quarters. The increase in intermediate good production increases the marginal return to capital and thus the capital rental rate, thus investment increases about 0.2% on impact and about 0.6% after 5 quarters before slowly returning back to its steady state.

In summary, the matching efficiency shock leads to a business cycle boom with increasing output, investment and consumption, as well as decreasing unemployment. These results are consistent with the findings in Furlanetto and Groshenny (2016). However, a typical feature of business cycles is also comovement in real wages, while after a positive matching efficiency shock real wages first decline. Consequently and in line with the findings of the variance decomposition, matching efficiency shocks are unlikely to be the major driver of the business cycle. However, as the main body of the paper showed, the huge negative matching efficiency shock during the Great Recession was a strong contributor to the decline in endogenous TFP growth at this time.

3 The long-run consequences of changes in the inflation target

3.1 Introduction

After most central banks hit the Zero Lower Bound during the Great Recession, there was a discussion about if the target inflation rate and thus long-run average inflation should be raised, in order to attain a higher average nominal interest rate (given the Fisher equation $I = r + \pi$, with I the nominal interest rate, r the real interest rate and π the inflation rate and given the classical assumption that the real interest rate is not affected by nominal quantities in the long run, the average nominal interest rate is directly proportional to the long-run average inflation rate) and give central banks more space for monetary policy before they encounter the Zero Lower Bound[1]. However, for instance Coibion et al. (2012) show that in standard business cycle models, from a welfare optimization point of view, the optimal inflation target remains low, even if it means that the economy hits the Zero Lower Bound more often (in fact they show that the welfare costs of high positive average inflation itself are higher than the welfare costs incurred by an overall unlikely event like an encounter with the Zero Lower Bound).

In light of the recent work by Moran and Queralto (2018) or Bianchi et al. (2019), who study the influence of monetary policy shocks on technological progress in a Newkeynesian model with endogenous growth and find that a negative monetary policy shock leads to an increase in longer-run technological progress, the present paper adds another layer to the discussion about higher inflation targets by studying their long-run consequences. While both, negative monetary policy and positive inflation target shocks, are considered to be expansionary monetary policy, inflation target shocks discern from classical monetary policy shocks, as a positive inflation target shock implies increasing inflation and nominal interest rates at the same time, while a classical negative monetary policy shock implies decreasing nominal interest rates and increasing inflation. Another difference assumed in the present paper is that exogenous deviations from the policy rule of the central bank can only be attributed to a monetary policy shock in the very short run. If the central bank deviates from its rule for a longer time, it has to be an exogenous change in their policy target and not just short-run "craziness". Thus, the findings of Moran and Queralto (2018) or Bianchi et al. (2019) regarding monetary policy shocks are not

[1]for the discussion see Blanchard et al. (2010) or Ascari and Sbordone (2014) for a survey

automatically valid for inflation target shocks as well. In order to study the long-run consequences of inflation target shocks, the present paper proposes a Newkeynesian model featuring endogenous TFP growth via R&D and technology adoption as in Comin and Gertler (2006), intermediate firms subject to quadratic price adjustment costs as in Rotemberg (1982) and a central bank following a Taylor Rule with a fluctuating inflation target as in Ireland (2007). The model is then estimated using Bayesian methods. It turns out that permanently increasing the inflation target about 5%, which would have been required to avoid the Zero Lower Bound during the Great Recession[2], reduces TFP permanently by over 0.05%. If the inflation target shock is only transitory, TFP recovers in the medium run. However, using transitory inflation target shocks to defend against the Zero Lower Bound would require to predict an encounter with it beforehand, which might not be an easy task and renders inflation target policy a difficult instrument to hedge against the Zero Lower Bound.

The mechanism is as follows: If the inflation target increases exogenously, expected and thus also current inflation increases. The central bank does not counteract the inflationary pressure and in response increases the nominal interest rate by less than the increase in the inflation rate in order to reduce the real interest rate, which leads to an increase in demand and thus again a higher inflation rate. Intermediate goods firms, who are monopolistic suppliers of their respective intermediate good, are subject to nominal rigidities and the upcoming inflation then, as common in Newkeynesian models, reduces their price markup. Furthermore, intermediate good firms are in Schumpeterian competition with outside firms for the position as incumbent, who is the only firm actually producing and selling the respective intermediate good and where only the firm with the highest attained quality can be the market incumbent in the next period of time. To attain a higher quality, firms have to invest in new technologies, which are invented by the R&D sector and subsequently adopted by the technology adopter. Under free entry to the innovation competition for next period's market incumbent, firms will have to spend the expected discounted value of being the market incumbent for their innovation investment, as spending more yields a negative intertemporal value of participating in the innovation contest, while spending less is a guaranteed loss where the firm invests in technology without getting the position as incumbent, thus not partic-

[2]Blanchard et al. (2010) state that the FED would have liked to reduce the FFR about additional 2-5% during the Great Recession. From the model, a permanent one standard deviation shock to the inflation target would induce a 5% higher nominal interest rate, which is in the aforementioned range and is thus taken as the reference interest rate increase in the present paper.

ipating in the contest is a better option in this case. The reduction in the price markup following the sudden increase in the inflation rate reduces future expected sales revenues for the intermediate firms and makes it less attractive for both incumbents and outside competitors to participate in the innovation contest. Thus, the overall technological progress is slowed down and TFP growth is lower than without the inflation target shock. If the central bank reverts back to its previous inflation target, this induces a period of slow disinflation, marginally lower wages, a slight increase in the price markup and thus an increase in the future value of becoming the incumbent. The higher innovation incentive during this time leads to a long-run recovery of the initial negative TFP effect of the inflation target shock. However, if the inflation target shock is permanent, average inflation will be higher permanently and thus the recovery period will not take place. Consequently, a permanent increase in the inflation target might help to hedge against the event of hitting the Zero Lower Bound, but comes with a long-run cost in form of a permanent reduction in TFP.

How does this paper fit into the related literature? There is a vast amount of papers finding a negative effect of inflation on subsequent economic growth within and across countries[3], which supports the present paper's prediction that permanent positive inflation target shocks create higher average inflation and a medium-run decrease in TFP growth. Despite the empirical evidence being quite clear, there is still an ongoing debate about the exact transmission channel behind this finding. For instance Annicchiarico et al. (2011) and Annicchiarico and Rossi (2013) argue that higher inflation volatility increases uncertainty and reduces investment, which in an AK-type model leads to lower growth. Chu et al. (2015) argue that R&D is subject to a cash-in-advance constraint, where inflation decreases the real value of cash and thus the R&D level, which in turn decreases technological progress. Additionally, recent research hints that a higher nominal interest rate is associated with a slowdown in R&D, which is another prediction of the present paper's model. For example Chu and Cozzi (2014) find an increasing nominal interest rate to be connected with decreasing R&D effort in a model with a cash-in-advance constraint on R&D. What sets apart traditional monetary policy shocks and inflation target shocks is that in consequence of an increase in the nominal interest rate the former leads to a decrease in the inflation rate, while the latter leads to an increase. The present paper is also closely related to Moran and Queralto (2018) and Bianchi et al. (2019), who find that a monetary policy shock (so an exogenous increase in

[3] see Bick (2010), Bruno and Easterly (1996), Bruno and Easterly (1998), Kremer et al. (2013), Vaona and Schiavo (2007) or Omay and Kan (2010)

the nominal interest rate without affecting the inflation target) is associated with lower TFP growth, as the higher discounting on future profits and lower overall demand reduces the incentive of current research. However, their approach is not able to explain the negative relation between inflation and economic growth, in fact it predicts a positive relation. An inflation target shock also leads to an increase in the nominal interest rate and a decrease in the TFP growth rate, however associated with increasing inflation. Thus, the model proposed in the present paper is able to capture both of the two empirical observations: First a monetary policy shock and an inflation target shock will induce an increasing nominal interest rate, where in both cases TFP growth will decline. Second a long-run increase in the inflation rate following an inflation target shock will lead to a long-run loss in TFP and income.

Furthermore, the present paper is loosely related to the recent literature around Anzoategui et al. (2019), Benigno and Fornaro (2017) and Guerron-Quintana and Jinnai (2019), who introduce endogenous growth induced by R&D and technology adoption into standard business cycle models and Garga and Singh (2021), who discuss optimal monetary policy including TFP growth as an additional objective. The present paper is complementary to this literature by additionally analyzing the effect of inflation target shocks, as discussed by for instance Smets and Wouters (2003) and Ireland (2007), on technological progress. The papers mentioned above rely on technology adoption as a mechanism to propagate short-run shock effects to the medium run and thus create a sluggish reaction of productivity to high-frequency shocks. The present paper also uses this mechanism to create sluggish and highly persistent reactions of TFP to monetary policy and inflation target shocks.

The remainder of this paper proceeds as follows: Section 2 presents the model and discusses the main mechanisms that drive the results mentioned earlier. In section 3 the model is estimated using Bayesian methods and the resulting model impulse responses of TFP and related variables to temporary and permanent inflation target shocks are analyzed. Section 4 concludes.

3.2 The model

The model proposed here features a central bank following a Taylor Rule with a fluctuating inflation target as in Smets and Wouters (2003) and Ireland (2007). Furthermore, trend TFP growth is endogenous following a quality ladder as in Grossman and Helpman (1991). Endogenous growth models either use models of vertical growth, as implied by the quality ladder assumption for the model at hand, or horizontal growth, like in love for variety models. However, horizontal growth models typically imply a growing number of firms, where each firm comes into existence with a newly created patent. The increasing number of firms then leads to increasing competition between the firms and thus constantly decreasing intermediate goods prices. For the purpose of the model here, this is an undesirable feature, as imposing quadratic price adjustment costs on constantly decreasing goods prices with at the same time constant aggregate inflation yields positive price adjustment costs in the steady state, which makes the analysis more cumbersome. Moran and Queralto (2018) solve this problem by moving away price rigidity from intermediate goods producers to a retail sector, thus the nominal price for final goods is moved away from the growing firm number. However, this is again undesirable as it also moves away the markup reduction effect inflation has in Newkeynesian models from the intermediate firms, which is later shown to have an important effect on the innovation decision of the firms. For technological progress itself, both types of growth models have similar implications. Thus, the assumption of vertical growth is without loss of generality for that matter, but allows to impose an otherwise standard Newkeynesian model.

Intermediate goods firms are in Schumpeterian competition for the position in the market, where only the firms with the highest quality can be the incumbents[4]. In this setup, the competition for the place as incumbent producer is crucial for the innovation decision of the firms[5]. New technologies are produced by an R&D sector and subsequently adopted for usage in production by a technology adopter as in Comin and Gertler (2006), Benigno and Fornaro (2017) or Anzoategui et al. (2019). Each period there is a given incumbent, who in this period can produce and sell its respective intermediate good. But in each period there is also competition for the spot as market incumbent in the next period between the current incumbent and outside firms, where this spot is attained by the firm that invests the highest amount into new technologies compared to its competitors. Free entry to the innovation race dictates that the winning firm has to invest the expected discounted value of being next period's incumbent into new technologies. Investing less means that another firm can invest more and make positive intertemporal profits from becoming next period's incumbent, while investing more yields a negative intertemporal value of competing in the innovation race, thus not participating is a better option.

[4]see Olley and Pakes (1996)

[5]evidence for this found by Arrow (1962), Blundell et al. (1995) and Nickell (1996)

All intermediate firms are subject to quadratic price adjustment costs, as proposed by Rotemberg (1982), with indexation to a mix of the current inflation target and past inflation, as in Ireland (2007). As usual, upcoming inflation in this type of model reduces price markups and thus the expected discounted value of being next period's incumbent. Consequently, all firms have a lower incentive to participate in the innovation race and equilibrium innovation investment and technological progress will decrease in response to an inflation target shock.

3.2.1 Central bank

The central bank reacts to deviations of inflation from its target level and to deviations of employment[6] from its steady state level by following a Taylor Rule of the form

$$r_t = \bar{r} \left(\frac{\pi_t}{\pi_t^T} \right)^{\omega^\pi} \left(\frac{n_t}{\bar{n}} \right)^{\omega^n} exp(\varepsilon_t^r), \quad \omega^\pi > 0, \omega^n > 0, \tag{3.1}$$

where r_t is the real interest rate, $\bar{r}$ is the steady state level of the real interest rate, π_t is the inflation rate, π_t^T is the target inflation rate, n_t is employment, $\bar{n}$ is steady state employment and ε_t^r is an exogenous i.i.d. shock to the interest rate that will be called a monetary policy shock for convenience. The target inflation rate follows

$$\pi_t^T = \bar{\pi}^T exp(f_t), \quad \bar{\pi}^T \geq 0, \tag{3.2}$$

where $\bar{\pi}_t^T$ is the steady state inflation target and f_t are fluctuations of the central bank's inflation target. To distinguish monetary policy shocks from inflation target shocks, the modeling follows Smets and Wouters (2003) and assumes that monetary policy shocks are non-persistent, while inflation target shocks are persistent by assuming

$$f_t = \rho^f f_{t-1} + \varepsilon_t^\pi, \quad \rho^f \in (0, 1), \tag{3.3}$$

with ε_t^π an exogenous i.i.d. shock to the inflation target. Assuming that a monetary policy shock is a one-time event is just for convenience and not necessary for the model mechanism at hand. What is important is that the persistence of the monetary policy shock is lower than the speed of intermediate firms in implementing new technologies into their production process. For instance Bilbiie et al. (2012) assume a time-to-build lag for a new technology to be embodied within a firm. The model mechanism requires monetary policy shocks to have a lower persistence than

[6]where in this model employment also coincides with detrended output, see the appendix for the derivation.

this time-to-build lag. The intuition is as follows: As described in the introductory passage of the modeling section, positive inflation target shocks affect technological progress by decreasing the expected future intermediate price markups, which reduces technological progress. Moran and Queralto (2018) mute this markup effect by moving away the price rigidity to another sector, so a higher interest rate decreases demand and increases discounting of expected future profits, thus firms have a lower incentive to participate in the innovation contest. This allows them to have a clear negative effect of a positive monetary policy shock on technological progress. If there is a time-to-build lag, firms will not base their innovation decision on the expected value of winning the innovation contest for the next period, but on the expected value of being the incumbent after the time-to-build lag has passed. Thus, assuming that the monetary policy shock has a lower persistence than the speed of intermediate firms in implementing new ideas, essentially mutes the markup effect of monetary policy shocks regarding the innovation decision as well. Higher inflation induced by an inflation target shock for that matter will persistently reduce future price markups and lower the incentive to participate in the innovation contest.

3.2.2 R&D sector

The R&D sector produces new unadopted ideas R_t according to the production function

$$R_t = \chi \left(\frac{X_t}{q_t} \right)^{1-\kappa} \mathcal{U}_{t-1}^{\mu_x}, \quad \chi > 0, \kappa \in (0,1), \mu_x \in (0,1), \tag{3.4}$$

where X_t is real R&D spending and q_t is the aggregate TFP level. The R&D spending is deflated by the TFP level to ensure the existence of a balanced growth path and resembles the idea that it becomes more difficult for advanced economies to push forward their innovation frontier[7]. As the economy grows, the means to spend on research increase and without any counteracting force, research spending and ultimately technological progress would explode. For instance Comin and Gertler (2006) impose that there is a congestion externality, where the aggregate amount of research spending decreases the productivity of individual research spending. Anzoategui et al. (2019) see the congesting factor in the provision of skilled labor, where higher employment of skilled labor reduces the productivity of each skilled worker within the research process. All of these variables are ultimately correlated

[7] empirical evidence for the real world existence of this mechanism is provided by Griliches (1990)

with aggregate productivity and as the present paper wants to stay agnostic about the exact research process, aggregate productivity is used as a proxy for whatever might reduce the productivity of research spending along the balanced growth path. Furthermore, following Romer (1990) and Moran and Queralto (2018), there is a spillover from the total stock of ideas $\mathcal{U}_{t-1}$ such that more existing ideas benefit the research of new ideas.

The R&D sector sells new unadopted ideas R_t to the licenser at competitive price p_t^R, so the maximization problem reads

$$\max_{X_t} \Gamma_t = p_t^R R_t - X_t \tag{3.5}$$

subject to (3.4), which yields the first order condition

$$\frac{p_t^R}{q_t}\chi(1-\kappa)\mathcal{U}_{t-1}^{\mu_x} = \left(\frac{X_t}{q_t}\right)^{\kappa}, \tag{3.6}$$

so the real spending on R&D depends positively on the price of new unadopted ideas and the stock of unadopted ideas.

3.2.3 Licenser

The licenser accumulates a stock of unadopted ideas $\mathcal{U}_t$ by buying new unadopted ideas R_t from the R&D sector and sells licenses for technology adoption to the technology adopters at competitive price $p_t^{\mathcal{U}}$ that may result in Δ_t^A of the unadopted ideas becoming adopted. So the stock of unadopted ideas evolves according to

$$\mathcal{U}_t = (1-\delta^{\mathcal{U}})\mathcal{U}_{t-1} + R_t - \Delta_t^A, \quad \delta^{\mathcal{U}} \in (0,1), \tag{3.7}$$

where $\delta^{\mathcal{U}}$ is the obsolescence rate of unadopted ideas. Thus, the optimization problem of the licenser reads

$$\max_{R_t} E_t \sum_{s=0}^{\infty} \Lambda_{t,t+s}\Xi_{t+s} = E_t \sum_{s=0}^{\infty} \Lambda_{t,t+s}\left(p_{t+s}^{\mathcal{U}}\mathcal{U}_{t+s-1} - p_{t+s}^R R_{t+s}\right), \tag{3.8}$$

with E_t the expectation operator and $\Lambda_{t,t+s}$ the stochastic discount factor between periods t and $t+s$, which is subject to (3.7). Consequently, the first order condition of the licenser reads

$$p_t^R = E_t \Lambda_{t,t+1} p_{t+1}^{\mathcal{U}} \tag{3.9}$$

such that the expected discounted license price equals the current price of new unadopted ideas.

3.2.4 Technology adopter

The technology adopter buys a license for the usage of an unadopted idea in the adoption process from the licenser at price $p_t^{\mathcal{U}}$. The success probability for adopting an unadopted idea and thus the speed of diffusion between unadopted and adopted technologies is given by $\phi(\Upsilon_t) = \left(\frac{\Upsilon_t}{q_t}\right)^{1-\xi}$, where Υ_t is real adoption effort, which is also deflated by the current TFP level to ensure the existence of a balanced growth path, resembling the idea that it becomes more and more difficult to adopt new technologies for advanced economies. Again, as the economy grows there are more and more means to spend on technology adoption, thus the effectiveness of adoption spending has to decrease along the balanced growth path to ensure stability. Consequently, new adopted technologies Δ_t^A per period are given by

$$\Delta_t^A = \left(\frac{\Upsilon_t}{q_t}\right)^{1-\xi} \mathcal{U}_{t-1}, \quad \xi \in (0,1). \tag{3.10}$$

The technology adopter sells newly adopted ideas to the intermediate goods firms at competitive price p_t^A, so its optimization problem reads

$$\max_{\Upsilon_t, \mathcal{U}_{t-1}} \Omega_t = p_t^A \Delta_t^A - p_t^{\mathcal{U}} \mathcal{U}_{t-1} - \Upsilon_t \tag{3.11}$$

and thus the first order conditions are

$$\frac{p_t^A}{q_t}(1-\xi)\mathcal{U}_{t-1} = \left(\frac{\Upsilon_t}{q_t}\right)^{\xi} \tag{3.12}$$

$$p_t^A \left(\frac{\Upsilon_t}{q_t}\right)^{1-\xi} = p_t^{\mathcal{U}}. \tag{3.13}$$

Equation (3.12) gives the optimal input relation between adoption effort and unadopted ideas at a given price p_t^A, where a higher ratio of adoption spending compared to the stock of unadopted ideas has to be associated with a higher price for adopted technologies. Equation (3.13) gives the optimal adoption effort depending on the price ratio between unadopted and adopted technologies, where with a higher price of unadopted ideas in relation to adopted ideas the technology adopter will choose to increase the adoption rate rather than to acquire new unadopted ideas.

3.2.5 Final goods producer

The final goods sector follows the standard Blanchard and Kiyotaki (1987) approach. There is a continuum of intermediate goods firms of mass 1, each selling a unique intermediate good to the final goods producer, who uses them to produce a single final good, which is sold at price P_t to the households. The price aggregate reads

$$P_t = \left(\int_0^1 p_{i,t}^{1-\varepsilon} di \right)^{\frac{1}{1-\varepsilon}}, \quad \varepsilon > 0, \tag{3.14}$$

where $p_{i,t}$ is the price of intermediate good i. The final good is produced subject to a CES aggregate of the form

$$Y_t = \left(\int_0^1 y_{i,t}^{\frac{\varepsilon-1}{\varepsilon}} di \right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{3.15}$$

so the optimization problem of the final goods producer reads

$$D_t^f = \left(\int_0^1 p_{i,t}^{1-\varepsilon} di \right)^{\frac{1}{1-\varepsilon}} \left(\int_0^1 y_{i,t}^{\frac{\varepsilon-1}{\varepsilon}} di \right)^{\frac{\varepsilon}{\varepsilon-1}} - \int_0^1 p_{i,t} y_{i,t} di \tag{3.16}$$

and thus the first order condition is

$$y_{i,t} = \left(\frac{p_{i,t}}{P_t} \right)^{-\varepsilon} Y_t \tag{3.17}$$

such that the demand for intermediate good $y_{i,t}$ is negatively dependent on its real price $\frac{p_{i,t}}{P_t}$, where ε parameterizes the price elasticity of demand, and positively dependent on the aggregate income level.

3.2.6 Intermediate goods producer

Each intermediate good firm i produces a differentiated intermediate good under the production function

$$y_{i,t} = q_{i,t} n_{i,t}, \tag{3.18}$$

where $n_{i,t}$ is the labor input and $q_{i,t}$ the productivity level of firm i. The individual productivity level follows a quality ladder, as in Grossman and Helpman (1991), of the form

$$q_{i,t} = \lambda^{A_{i,t-1}} exp(e_t), \quad \lambda > 1, \tag{3.19}$$

where $A_{i,t-1}$ is the stock of adopted technologies accumulated by firm i, where the stock of adopted technologies follows the law of motion

$$A_{i,t} = A_{i,t-1} + \Delta^A_{i,t} \tag{3.20}$$

and e_t are exogenous fluctuations of the aggregate productivity level following the autoregressive law of motion

$$e_t = \rho^e e_{t-1} + \varepsilon^q_t, \quad \rho^e \in (0,1), \tag{3.21}$$

where ε^q_t is an i.i.d. aggregate TFP shock.

Intermediate firms are monopolistic suppliers of their respective intermediate good $y_{i,t}$ and sell it at price $p_{i,t}$. For production, they hire labor at real wage W_t and spend $p^A_t \Delta^A_{i,t}$ units on productivity enhancements that lead to a higher productivity level in the future. Furthermore, the intermediate firms are subject to quadratic price adjustment costs following Rotemberg (1982). As in Ireland (2007), price adjustment costs with an indexation to past inflation and the central bank's inflation target are assumed and read

$$\Theta_{i,t} = \frac{\theta}{2}\left[\frac{p_{i,t}}{(1+\pi^T_t)^\iota (1+\pi_{t-1})^{1-\iota} p_{i,t-1}} - 1\right]^2 Y_t, \quad \theta > 0, \iota \in (0,1), \tag{3.22}$$

where ι is a parameter that measures how dependent on past inflation price adjustment costs of the intermediate firms are.

Between periods, there is Schumpeterian competition for the spot as incumbent, where each incumbent firm is challenged by outside competitors for its position in the market and only the firm with the highest quality level can stay in the market. Competitors can imitate the current state of technology without any cost, but incumbents and outside competitors alike have to innovate by buying new adopted technologies in order to increase the technology level. The firm that attains the highest productivity level, may it be current incumbent or outside competitor, will be the market incumbent during the next period. As the current productivity level can be imitated without any costs and as winning the innovation contest only saves the position as market incumbent for one period, the current status as market incumbent or outside competitor does not matter for the innovation decision. Define the period gain of being the incumbent as

$$\mathcal{M}_{i,t} = \frac{p_{i,t}}{P_t} y_{i,t} - W_t n_{i,t} - \Theta_{i,t}, \tag{3.23}$$

where W_t is the real wage. Innovation spending $p_t^A \Delta_{i,t}^A$ is dropped here, as current incumbents can always choose to set $p_t^A \Delta_{i,t}^A = 0$ and not participate in the innovation contest for next period's incumbent, thus innovation spending does not concern the current value of being the incumbent, but only the effort to become next period's incumbent. Free entry to the innovation contest for next period's incumbent dictates that the winning firm has to be the one spending the expected discounted value of being next period's incumbent. Spending more, yields a negative intertemporal value of participating in the innovation contest, as innovation costs are higher than the expected value of being next period's incumbent, while spending less is a guaranteed loss in the innovation contest, as another firm could spend marginally more on innovation and take the position as incumbent, leaving the firm with zero gain from participating in the innovation contest. Thus, in the optimum the winning firm of the innovation contest will spend the expected discounted value of being next period's incumbent that obtains under optimal behavior. Consequently, today's innovation spending of next period's incumbent reads

$$p_t^A \Delta_{i,t}^A = E_t \Lambda_{t,t+1} \mathcal{M}_{t+1}, \tag{3.24}$$

where the i index on next period's incumbent gains are dropped, because the winner of the innovation contest has to consider optimal behavior of all its competitors and base its innovation decision on the aggregate value of being next period's incumbent, which is exogenous to the individual firm. In consequence, the innovation decision itself is exogenous for the winning firm. Optimal innovation is thus at the indifference point between participating in the innovation contest or not participating. One firm will choose innovation spending as dictated by equation (3.24) and become next period's incumbent, while the others will withdraw from the innovation contest. In this model, it is unclear if always the same firm will stay incumbent or if there is continuous exchange. However, for the relevant model mechanisms the identity of next period's incumbent is irrelevant, as current incumbent and outside competitors are equal ex ante and have to consider the same restrictions and economic environment. Thus, for all practical means, the firms producing intermediate good i can be considered as one continuously incumbent firm that has to respect (3.24) as a constraint for its innovation spending, if one is not interested in the firm dynamics behind it.

Taking this into account, the innovation decision for the firm branch i is exogenously given by (3.24) and firms only have to decide about setting the optimal price $p_{i,t}$ in each period. Consequently, the profit maximization problem of the intermediate goods firm i reads

$$\max_{p_{i,t}} = E_t \sum_{s=0}^{\infty} \Lambda_{t,t+s} D^{im}_{i,t+s} = E_t \sum_{s=0}^{\infty} \Lambda_{t,t+s} \left(\frac{p_{i,t}}{P_t} y_{i,t} - W_t n_{i,t} - \Theta_{i,t} - p^A_t \Delta^A_{i,t} \right), \tag{3.25}$$

subject to (3.17), (3.18), (3.19), (3.20), (3.22) and (3.24). As ex post all incumbent firms are identical, firm indices can be dropped. Furthermore, define the inflation rate as $\pi_t = \frac{P_t}{P_{t-1}} - 1$, so the first order condition of the intermediate firms yields the Phillips Curve of the form

$$\begin{aligned} &\left[\frac{1+\pi_t}{(1+\pi^T_t)^{\iota}(1+\pi_{t-1})^{1-\iota}} - 1 \right] \frac{1+\pi_t}{(1+\pi^T_t)^{\iota}(1+\pi_{t-1})^{1-\iota}} = \frac{\varepsilon - 1}{\theta} \left[\frac{\varepsilon}{\varepsilon - 1} \frac{W_t}{q_t} - 1 \right] \\ &+ E_t \Lambda_{t,t+1} \left[\frac{1+\pi_{t+1}}{(1+\pi^T_{t+1})^{\iota}(1+\pi_t)^{1-\iota}} - 1 \right] (1+g^y_{t+1}) \frac{1+\pi_{t+1}}{(1+\pi^T_{t+1})^{\iota}(1+\pi_t)^{1-\iota}}, \end{aligned} \tag{3.26}$$

where $g^y_t = \frac{Y_t}{Y_{t-1}} - 1$ is the output growth rate. As usual the Phillips Curve says that current inflation depends on expected future inflation and the deviation of marginal production costs from their steady state level.

How do inflation target shocks affect the innovation decision of the firms? Note that by inserting (3.18) and (3.31) in the definition of $\mathcal{M}_{i,t}$ and by symmetry one can write

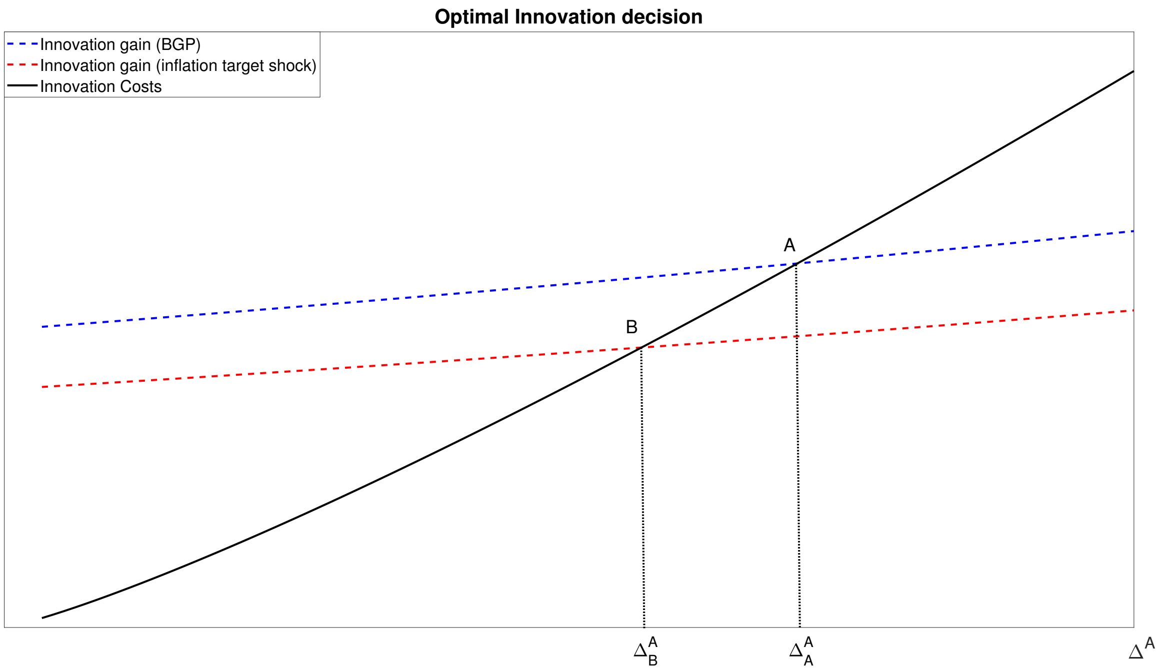
$$\begin{aligned} \mathcal{M}_t &= q_t n_t - n_t^{1+\varphi} q_t - \frac{\theta}{2} \left[\frac{1+\pi_t}{(1+\pi^T_t)^{\iota}(1+\pi_{t-1})^{1-\iota}} - 1 \right]^2 q_t n_t \\ &= q_t \left(n_t - n_t^{1+\varphi} - \frac{\theta}{2} \left[\frac{1+\pi_t}{(1+\pi^T_t)^{\iota}(1+\pi_{t-1})^{1-\iota}} - 1 \right]^2 n_t \right) = q_t \Psi(n_t, \pi_t, \pi^T_t), \end{aligned} \tag{3.27}$$

where $\Psi(n_t, \pi_t, \pi^T_t)$ are the detrended sales revenues minus price adjustment costs. Note further that $\frac{q_{t+1} - q_t}{q_t} \approx \ln(q_{t+1}) - \ln(q_t) = \ln(\lambda)\Delta^A_t$ and the stochastic discount factor simplifies to $\Lambda_{t,t+1} = \frac{1}{1+r_t}$, thus the expected discounted value of being next period's incumbent reads

$$E_t \Lambda_{t,t+1} \mathcal{M}_{t+1} = E_t \frac{1}{1+r_t} (1 + \ln(\lambda)\Delta^A_t) q_t \Psi(n_{t+1}, \pi_{t+1}, \pi^T_{t+1}), \tag{3.28}$$

where the term $= E_t \frac{1}{1+r_t}(1+\ln(\lambda)\Delta^A_t)\Psi(n_{t+1}, \pi_{t+1}, \pi^T_{t+1})$ should be stationary on the balanced growth path and only q_t is growing. Figure 3.1 schematically depicts the innovation gain, so the expected discounted value of being next period's incumbent, and innovation costs in dependence of the number of new technologies Δ^A_t that are about to be implemented. In order to have a unique interior optimum, the cost

Figure 3.1: Schematic depiction of innovation decision under an inflation target shock. The optimal amount of new implemented technologies Δ_t^A is at the intersection point A between the innovation gain and innovation cost curve. An inflation target shock leads to a decrease in discounting and a decrease in price markups and sales revenues, where the latter effect dominates the former. Thus, the gain curve is shifted downwards and the new intersection point between cost and gain curve at B implies a lower number of new adopted technologies implemented by the intermediate firms.



curve has to at first lie beneath the gain curve, but has a higher slope. According to equation (3.24), optimal innovation lies at the intersection of gain and cost curve, which on the balanced growth path is at point A, where the dashed blue line depicts the innovation gain on the balanced growth path and the black line the innovation costs. If the central bank wants to increase the inflation target, it has to work towards lowering the real interest rate in order to increase inflation. The decrease in the real interest rate itself lowers discounting and in consequence has a partially positive influence on the amount of innovation spending. However, from standard Newkeynesian theory one would expect an increase in the inflation rate to lead to a decrease in the price markup of firms and thus lower sales revenues, as the marginal production costs increase faster than the price for the intermediate goods, thus one would assume that $\frac{\partial \Psi(n_{t+1}, \pi_{t+1}, \pi_{t+1}^T)}{\partial \varepsilon_t^\pi} < 0$, which implies lower innovation spending. From the estimation of the model later on, it is evidenced that the latter effect is stronger than the former and an inflation target shock actually shifts the gain curve downwards (the dashed red line in the figure). Thus, the intersection point B between the new gain curve and the cost curve lies farther to the left and the number of new implemented technologies Δ_t^A decreases.

3.2.7 Household sector

The representative household maximizes its expected lifetime stream of utility given by

$$E_t \sum_{s=0}^{\infty} U_{t+s} = E_t \sum_{s=0}^{\infty} \beta^t exp(d_t) \left(\ln(C_{t+s}) - \frac{n_{t+s}^{1+\varphi}}{1+\varphi} \right), \quad \varphi > 0, \tag{3.29}$$

where β is the discount factor, $d_t = \rho^\beta d_{t-1} + \varepsilon_t^\beta$ are demand fluctuations with ε_t^β an exogenous i.i.d. consumer preference shock and C_t is the consumption level. Households are subject to their budget constraint, which in every period reads

$$C_t + B_t + T_t = W_t n_t + (1 + r_{t-1}) B_{t-1} + \Gamma_t + X_t + \Xi_t + \Omega_t + D_t^f + D_t^{im} + \Upsilon_t + \Theta_t, \tag{3.30}$$

where B_t are riskless government bonds and T_t is a lump-sum tax.

Consequently, the optimality conditions for the household read

$$n_t^\varphi = W_t C_t^{-1} \tag{3.31}$$

$$C_t^{-1} = E_t \beta \frac{exp(d_{t+1})}{exp(d_t)} (1 + r_t) C_{t+1}^{-1}, \tag{3.32}$$

where (3.31) is the usual labor supply condition, which says that the real wage is increasing in labor and the consumption level. Equation (3.32) is the standard Euler equation, which implies that households will smooth their consumption path depending on the real interest rate and household discounting.

3.2.8 Government budget and aggregate resource constraint

To close the model, a simple government budget constraint is assumed, where the government just collects lump-sum taxes T_t and incurs new government debt B_t to pay off previous government debt B_{t-1} and the interest on it, so the government budget constraint reads

$$T_t + B_t = (1 + r_{t-1}) B_{t-1}. \tag{3.33}$$

Putting together the resource constraints of all sectors yields the aggregate resource constraint, which in this case reads

$$Y_t = C_t. \tag{3.34}$$

3.2.9 Equilibrium

By symmetry, all individual intermediate firms will behave the same, so the i-index can be dropped. The equilibrium is given by the sequence of variables

$$\Big\{ R_{t+s}, X_{t+s}, q_{t+s}, p^R_{t+s}, \mathcal{U}_{t+s}, \Delta^A_{t+s}, \Lambda_{t,t+s}, p^{\mathcal{U}}_{t+s}, r_{t+s}, \Upsilon_{t+s}, p^A_{t+s}, A_{t+s}, \pi_{t+s}, \pi^T_{t+s}, \\ f_{t+s}, n_{t+s}, e_{t+s}, \mathcal{M}_{t+s}, W_{t+s}, C_{t+s}, \beta_{t+s}, d_{t+s}, Y_{t+s}, g^y_{t+s} \Big\}_{s=0}^{\infty} \tag{3.35}$$

that fulfill the following set of equilibrium conditions

$$r_t = \bar{r} \left(\frac{\pi_t}{\pi^T_t} \right)^{\omega^\pi} \left(\frac{n_t}{\bar{n}} \right)^{\omega^n} exp(\varepsilon^r_t) \tag{3.36}$$

$$\pi^T_t = \bar{\pi^T} exp(f_t) \tag{3.37}$$

$$f_t = \rho^f f_{t-1} + \varepsilon^\pi_t \tag{3.38}$$

$$R_t = \chi \left(\frac{X_t}{q_t} \right)^{1-\kappa} \mathcal{U}^{\mu_x}_{t-1} \tag{3.39}$$

$$\frac{p^R_t}{q_t} \chi (1-\kappa) \mathcal{U}^{\mu_x}_{t-1} = \left(\frac{X_t}{q_t} \right)^{\kappa} \tag{3.40}$$

$$\mathcal{U}_t = (1 - \delta^{\mathcal{U}}) \mathcal{U}_{t-1} + R_t - \Delta^A_t \tag{3.41}$$

$$p^R_t = E_t \Lambda_{t,t+1} p^{\mathcal{U}}_{t+1} \tag{3.42}$$

$$\Delta^A_t = \left(\frac{\Upsilon_t}{q_t} \right)^{1-\xi} \mathcal{U}_{t-1} \tag{3.43}$$

$$\frac{p^A_t}{q_t} (1-\xi) \mathcal{U}_{t-1} = \left(\frac{\Upsilon_t}{q_t} \right)^{\xi} \tag{3.44}$$

$$p^A_t \left(\frac{\Upsilon_t}{q_t} \right)^{1-\xi} = p^{\mathcal{U}}_t \tag{3.45}$$

$$Y_t = q_t n_t \tag{3.46}$$

$$q_t = \lambda^{A_{t-1}} exp(e_t) \tag{3.47}$$

$$A_t = A_{t-1} + \Delta^A_t \tag{3.48}$$

$$e_t = \rho^e e_{t-1} + \varepsilon^q_t \tag{3.49}$$

$$\mathcal{M}_t = Y_t - W_t n_t - \frac{\theta}{2}\left[\frac{1+\pi_t}{(1+\pi_t^T)^\iota(1+\pi_{t-1})^{1-\iota}} - 1\right]^2 Y_t \tag{3.50}$$

$$p_t^A \Delta_t^A = E_t \Lambda_{t,t+1} \mathcal{M}_{t+1} \tag{3.51}$$

$$g_t^y = \frac{Y_t}{Y_{t-1}} - 1 \tag{3.52}$$

$$\begin{aligned}\left[\frac{1+\pi_t}{(1+\pi_t^T)^\iota(1+\pi_{t-1})^{1-\iota}} - 1\right]\frac{1+\pi_t}{(1+\pi_t^T)^\iota(1+\pi_{t-1})^{1-\iota}} &= \frac{\varepsilon-1}{\theta}\left[\frac{\varepsilon}{\varepsilon-1}\frac{W_t}{q_t} - 1\right] \\ + E_t\Lambda_{t,t+1}\left[\frac{1+\pi_{t+1}}{(1+\pi_{t+1}^T)^\iota(1+\pi_t)^{1-\iota}} - 1\right](1+g_{t+1}^y)\frac{1+\pi_{t+1}}{(1+\pi_{t+1}^T)^\iota(1+\pi_t)^{1-\iota}}\end{aligned} \tag{3.53}$$

$$n_t^\varphi = W_t C_t^{-1} \tag{3.54}$$

$$C_t^{-1} = \beta \frac{exp(d_{t+1})}{exp(d_t)}(1+r_t)C_{t+1}^{-1} \tag{3.55}$$

$$d_t = \rho^\beta d_{t-1} + \varepsilon_t^\beta \tag{3.56}$$

$$\Lambda_{t,t+1} = \frac{1}{1+r_t} \tag{3.57}$$

$$Y_t = C_t \tag{3.58}$$

The economy has a balanced growth path, where all growing variables grow at a common rate $g_{t-1}^{qt} = \ln(q_{t-1}^t) - \ln(q_{t-2}^t) = \ln(\lambda)\Delta_{t-1}^A$. In the appendix, this trend growth rate, detrended form and steady state of the model are derived, which are used to numerically solve the model using Dynare[8].

3.3 Bringing the model to the data

In this section the crucial parameters for the model mechanism proposed here are estimated using Bayesian methods. Looking at the impulse responses of TFP to inflation target and monetary policy shocks from the estimated model, it turns out that monetary policy shocks have a long-run negative effect on TFP as in Moran and Queralto (2018) and Bianchi et al. (2019). Inflation target shocks on the other side have a slightly stronger negative effect, but are only influential in the medium run with the shock effect fully degrading in the long run, if the shock is temporary, while the effect is permanent, if the inflation target increases permanently. This coincides with the findings of Bick (2010), Bruno and Easterly (1996), Bruno and Easterly (1998), Kremer et al. (2013), Vaona and Schiavo (2007) or Omay and Kan (2010), who find a negative relationship between inflation and long-run economic

[8]see Adjemian et al. (2011)

growth. The Dynare software is used for all estimations and simulations in the following section.

3.3.1 Calibration and parameter estimation

Some parameters are calibrated to either fit some moments of the data or according to standard values set by the literature. Table 3.1 sums up the externally calibrated parameters. The parameter χ is chosen such that the model steady state of the

Table 3.1: Calibrated Parameters

Parameter	Value	Source
χ	2.5	Matching mean R&D to GDP ratio of about 2.6%
π^T	0.005	Matching FED announced inflation target of 2%
ω^n	1	Moran and Queralto (2018)
λ	1.03	Matching technology hazard rate (Basu and Fernald (1997))
φ	0.5	Moran and Queralto (2018)
β	0.997	Matching mean FFR of about 4%

R&D spending to output ratio coincides with the observed mean R&D to GDP ratio of about 2.6% for the U.S. in the data. The discount factor β is calibrated such that the steady state nominal interest rate implied by the model equals the long-run mean Federal Funds Rate (FFR) of roughly 4%. The FED since 2012 follows a 2% p.a. inflation target and before that regularly announced a desired inflation rate, which was usually around 2% p.a. as well. As the model periodicity is set to quarterly, $\bar{\pi}^T$ is set to 0.005. The central bank's reaction parameter to the employment gap is set to 1 as in Moran and Queralto (2018). The inverse Frisch elasticity φ is set to 0.5, again as in Moran and Queralto (2018) and the technology hazard rate[9] λ is set to the standard value of 1.03 as evidenced by Basu and Fernald (1997).

For the estimation of the remaining parameters, five observable variables for the U.S. are considered: The TFP growth rate and output growth rate measured in % p.a. are provided by Fernald (2012-2019)[10]. The FFR measured in % p.a. is taken from the FRED (2019), but for the recent zero lower bound period the actual FFR

[9] The interpretation of λ as a hazard rate comes from the idea that each climb on the quality ladder replaces older vintages of a certain technology by newer ones, which increases productivity.

[10] where TFP is adjusted to be in line with the assumption of purely labor augmenting technological progress as in the model (as there is no capital) and not capital and labor augmenting technological progress as assumed by Fernald (2012-2019), so the residual between output growth and input factor growth that is defined as TFP growth by Fernald (2012-2019) is multiplied by $\frac{1}{1-\alpha}$. For a more thorough reasoning see the appendix.

is replaced by the shadow rate provided by Wu and Xia (2016). The inflation rate is defined as the annualized growth rate of the U.S. CPI. The fifth observable is the R&D expenditures to GDP ratio in percent, where both are also provided by the FRED (2019). All observables are in quarterly periodicity and are observed between 1960 and 2019. The observation equations in terms of the model variables (tildes denote detrended variables, the detrended model is given in the appendix) then read

$$TFP\_growth_t = (g^{qt}_{t-1} + e_t - e_{t-1}) \cdot 400 \tag{3.59}$$

$$Output\_growth_t = (g^{qt}_{t-1} + e_t - e_{t-1} + \ln(\tilde{Y}_t) - \ln(\tilde{Y}_{t-1})) \cdot 400 \tag{3.60}$$

$$R\&D\_ratio_t = \left(\frac{\tilde{X}_t}{\tilde{Y}_t} + \gamma_t \right) \cdot 100 \tag{3.61}$$

$$Inflation_t = \pi_t \cdot 400 \tag{3.62}$$

$$FFR_t = I_t \approx (r_t + \pi_t) \cdot 400, \tag{3.63}$$

where I_t is the nominal interest rate approximated by the Fisher equation and γ_t is an additional exogenous variable with the usual interpretation of a measurement error as R&D is notoriously hard to measure, which also avoids stochastic singularity as the number of structural shocks is smaller than the number of observed variables.

Table 3.2 summarizes the Prior distributions for the parameters to be estimated. The type of distributions mainly follows the suggestions of Smets and Wouters (2003). Consequently, the prior distributions for the estimated shock standard errors follow an Inverse Gamma distribution with a standard error of 2. The prior means are obtained by first preestimating the shock standard errors and then using the estimated mean as the prior mean in the second run. Also following Smets and Wouters (2003), the priors for the persistence parameters ρ^e and ρ^f follow a Beta distribution with mean 0.85 and standard error 0.1. Preestimations show that the persistence parameter for demand fluctuations is much lower than the other ones, thus the prior mean is set to about 1/3 to the respective other prior means, which appears to be more appropriate.

The parameter ω^π measures the reaction of the central bank to inflation deviating from its target level and is set to 0.5 by Moran and Queralto (2018), so this value is taken as the prior mean. The prior is assumed to follow a Normal distribution with a standard error of 0.25 to cover a 50% more or less aggressive reaction of the central bank to inflation. The parameter ι measures to what extent price adjustment costs

Table 3.2: Assumptions on prior distributions

Parameter	Type	Mean	Std. Error
ω^{π}	NORMAL	0.5	0.25
ι	BETA	0.5	0.15
ε	NORMAL	6	1
θ	NORMAL	98.81	10
κ	BETA	0.3	0.05
μ_x	BETA	0.7	0.05
ξ	BETA	0.075	0.05
$\delta^{\mathcal{U}}$	BETA	0.1	0.05
ρ^e	BETA	0.85	0.1
ρ^f	BETA	0.85	0.1
ρ^{β}	BETA	0.286	0.1
s.e. ε^{π}	INV. GAMMA	1.3	2
s.e. ε^{r}	INV. GAMMA	1.1	2
s.e. ε^{q}	INV. GAMMA	0.01	2
s.e. ε^{β}	INV. GAMMA	0.08	2
s.e. γ	INV. GAMMA	0.002	2

depend on the current inflation target and the past inflation rate. The parameter should be in the interval between 0 and 1, thus a Beta prior distribution is chosen. Ex ante a 50:50 mix is assumed, so the prior mean is set to 0.5, but as there is no strong evidence for this parameter, a broader prior with standard error 0.15 is chosen. The parameter ε determines the steady state markup set by intermediate firms. The commonly used value for this is 6 (see Ireland (2001)), which implies a steady state markup of 20%. The prior follows a Normal distribution with standard error 1, which translates into 5% more or less steady state markup. Using the formula provided by Keen and Wang (2007) [11], the (prior) values of β and ε with 20% reoptimizing firms per period translate into a value of 98.81 for the price stickiness factor θ. The prior follows a Normal distribution with standard error 10, which allows for a broad band of reasonable values. The following parameters should also lie in the range between 0 and 1, so a Beta prior is chosen respectively: Griliches (1990) estimates the elasticity of new ideas with respect to R&D spending κ to lie between 0.2 and 0.4, so the prior mean is set to 0.3. As there is clear evidence about the parameter, a narrow prior with standard error 0.05 is chosen. The parameter μ_x gives the strength of the spillover from the idea stock to the

[11] Keen and Wang (2007) show that the pricing parameter θ of the Rotemberg model can be calculated as $\theta = \frac{(\varepsilon-1)\eta}{(1-\eta)(1-\beta\eta)}$, where ε is the markup parameter, β the household's discounting factor as defined in the model and $1-\eta$ is the fraction of firms allowed to reoptimize and change their prices in a given period as in a Calvo model.

production of new ideas. Moran and Queralto (2018) estimate this value to be 0.7, so again as there is evidence about the parameter, a Beta prior with standard error 0.05 and mean 0.7 is chosen. The elasticity of the adoption probability with respect to adoption effort is given by $1 - \xi$. Anzoategui et al. (2019) estimate this parameter to be about 0.925, so ξ should be around 0.075. A Beta prior with mean 0.075 and standard error 0.05 is chosen accordingly. At last $\delta^{\mathcal{U}}$ measures the obsolescence rate of ideas, which is set to 0.1 by Moran and Queralto (2018), so a Beta prior with mean 0.1 and standard error 0.05 is chosen.

Table 3.3 sums up the resulting estimated posterior distributions of the parameters[12]. All parameters seem to be at reasonable values close to the related literature

Table 3.3: Properties of the posterior distributions

Parameter	Mode	Std. Error (Hessian)	5% (MH)	Mean (MH)	95% (MH)
ω^{π}	0.2922	0.1034	0.2133	0.2912	0.3706
ι	0.2731	0.0586	0.2199	0.2729	0.3242
ε	5.5007	0.1921	5.2467	5.6194	5.9624
θ	124.8911	1.6764	120.1526	129.4833	139.8270
κ	0.2880	0.0170	0.2566	0.2897	0.3286
μ_x	0.7439	0.0081	0.6610	0.7209	0.7772
ξ	0.0314	0.0168	0.0081	0.0456	0.0868
$\delta^{\mathcal{U}}$	0.0447	0.0184	0.0159	0.0506	0.0797
ρ^e	0.9966	0.0099	0.9936	0.9961	0.9987
ρ^f	0.9706	0.0099	0.9516	0.9687	0.9878
ρ^{β}	0.0249	0.0122	0.0124	0.0296	0.0474
s.e. ε^{π}	1.2808	0.2020	1.0529	1.3180	1.5778
s.e. ε^{r}	1.0928	0.1188	1.0127	1.1054	1.2001
s.e. ε^{q}	0.0115	0.0006	0.0106	0.0116	0.0125
s.e. ε^{β}	0.0797	0.0048	0.0733	0.0797	0.0869
s.e. γ	0.0022	0.0001	0.0020	0.0022	0.0025

at the posterior mode and mean. Figure 3.2 depicts the prior and posterior densities of the estimated model parameters, while figure 3.3 plots the prior and posterior densities of the estimated shock standard errors.

3.3.2 The effect of inflation target shocks on technological progress

In this section the impulse responses of technology related variables with respect to inflation target and monetary policy shocks are analyzed. In the appendix a

[12]Posterior distributions received by employing the Metropolis Hastings algorithm. The algorithm uses a Markov-Chain-Monte-Carlo (MCMC) simulation with 20,000 draws in total, while 10,000 draws are finally kept and another 10,000 draws discarded as burning-in draws.

Figure 3.2: Prior and posterior densities for the estimated parameters.

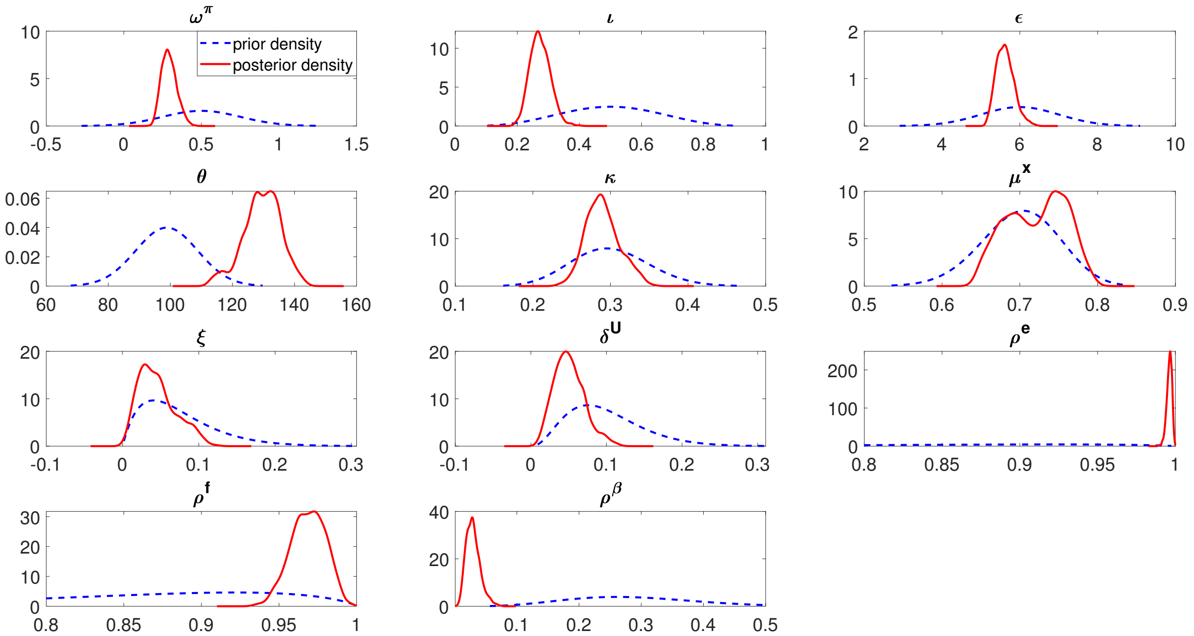
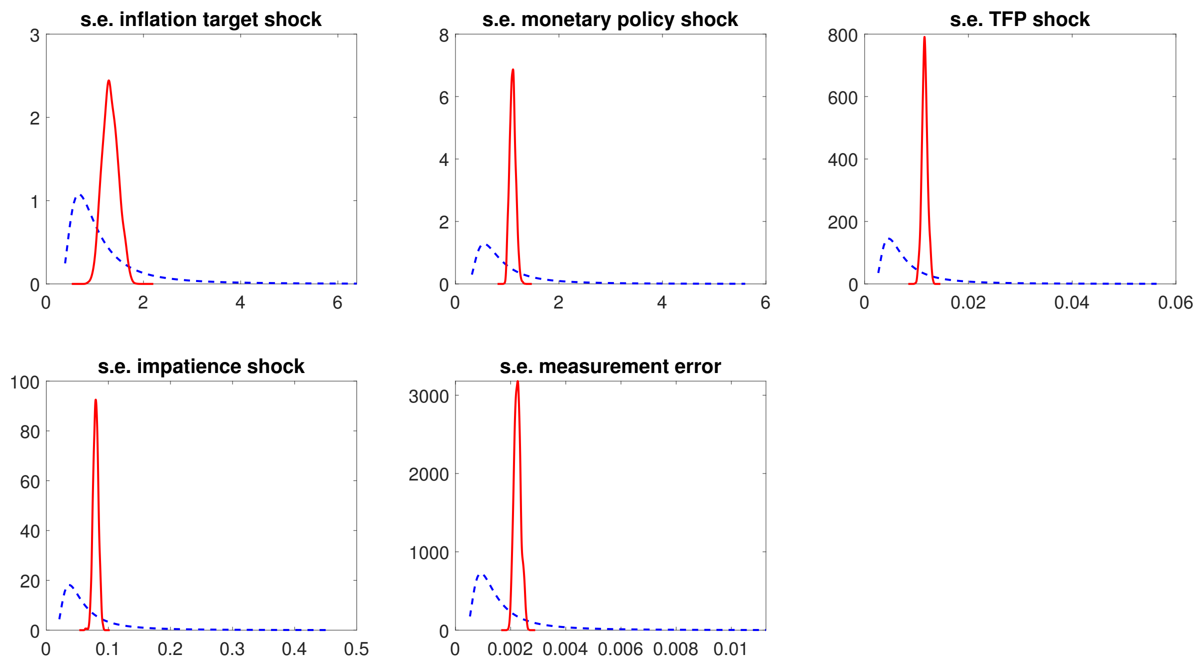
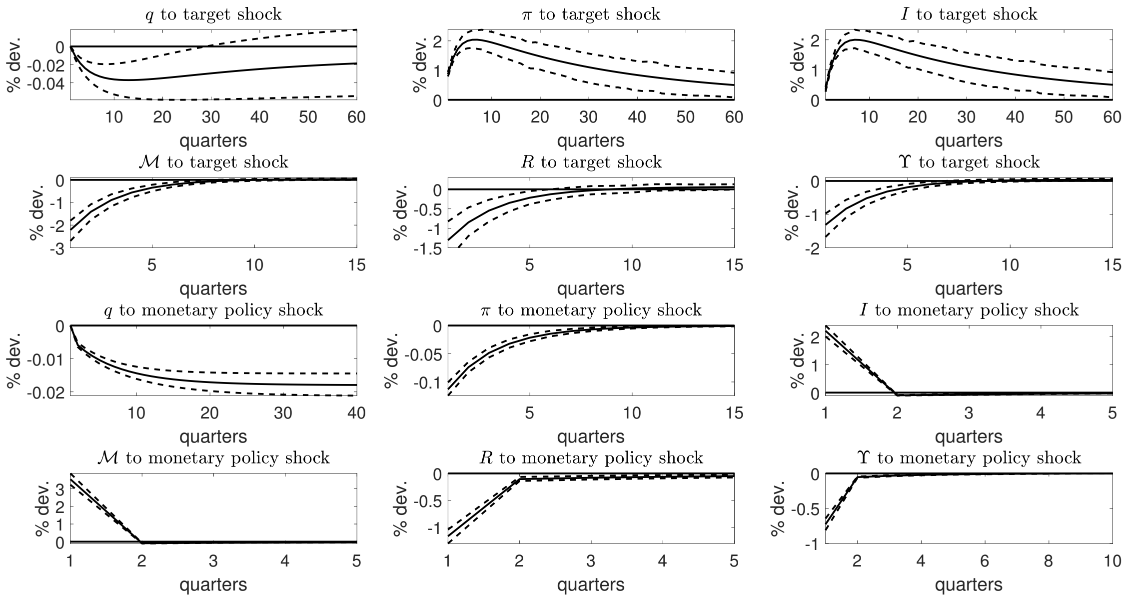


Figure 3.3: Prior and posterior densities for the estimated shock standard errors.



deeper discussion of the historical relevance of inflation target shocks and the effect of monetary policy and inflation target shocks on output, consumption, wages and the real interest rate is provided. Figure 3.4 shows the impulse responses of TFP q, inflation π, the nominal interest rate I, the period gain of being an incumbent $\mathcal{M}$, the production of unadopted ideas R and the adoption effort Υ to a transitory inflation target and monetary policy shock of size one standard deviation (which translates into a change of about 5 percentage points in the inflation target and a change of 0.5 percentage points in the real interest rate respectively). As it can be

Figure 3.4: Impulse responses to a 1 standard deviation increase in inflation target and FFR as implied by the model. The dashed lines show the 90% credible intervals based on the highest posterior density interval (HPDI).

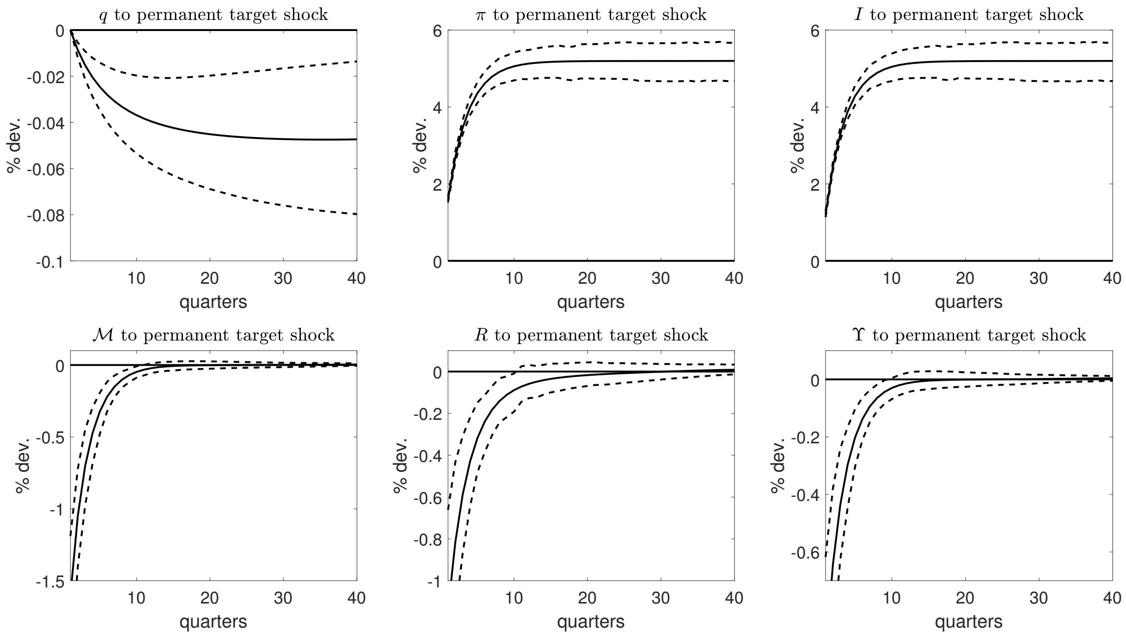


seen, regarding a monetary policy shock the results are qualitatively quite similar, though quantitatively weaker, to the findings in Moran and Queralto (2018) and Bianchi et al. (2019). An exogenous increase in the real interest rate leads to a long-run decrease in the TFP level of nearly 0.02% after 20 quarters. What is the intuition behind this? After the monetary policy shock hits the economy, inflation decreases by over 0.1% on impact and consequently the period gain of being the incumbent increases by over 3% on impact. However, this is a one time event and the expected future gain (so here after more than one period) of being the incumbent is not changing. On the other side, the higher interest rate increases discounting of the future expected gain of being the incumbent, so the incentive to participate in the innovation contest is actually decreasing, thus adoption effort decreases by over 0.6% on impact and the production of new unadopted ideas decreases by nearly 1%, so overall technological progress slows down.

On the other side, a temporary inflation target shock leads to a quick decline of TFP by nearly 0.03% within the first three years. The negative shock effect then is slowly reverted, but is not fully recovered even after 15 years have passed, when TFP is still 0.02% lower than without the shock. How is this behavior explained? As it can be seen, the inflation target shock leads to a nearly 2% higher inflation within the first three years and the central bank will increase the nominal interest rate about nearly 2% within the first two years, reverting back to the steady state level over more than 15 years. The increase in inflation leads to a drop in the period gain of being the incumbent of nearly 2%, which now in contrast to the monetary policy shock is persistent and outweighs the lower discounting from the lower real interest rate. As the markup effect is stronger than the discounting effect, this leads to a less attractive market entrance, so expenditures on innovation decrease. Consequently, adoption effort decreases by over 1% and production of new unadopted ideas decreases by nearly 1.5%. After about 10 quarters, inflation stops to increase and begins to slowly return to its steady state level. The subsequent period of slow disinflation leads to a slight recession, where wages are a bit lower, the price markup increases and the value of being next period's incumbent is slightly higher than on the balanced growth path (see the appendix for further details). As it can be seen, the impulse response of adoption effort and idea production is slightly above zero after 10 quarters, allowing for the slow return of TFP to its steady state level, where the shock effect becomes insignificant after about 30 quarters.

It should be noted that the slow recovery of TFP is only possible because the inflation target returns back to its steady state level and thus allows for a period of time, where inflation is decreasing. If the inflation target shock is permanent as in Ireland (2007), inflation does not revert back to the old target level after reaching the new one, thus there is no recovery period and TFP stays on the lower level. Figure 3.5 shows the impulse responses of the variables mentioned above if the inflation target shock of the same size is permanent. As it can be seen, long-run trend inflation increases about 5%. As the real interest rate is constant on the long-run balanced growth path, the nominal interest rate is also about 5% higher than before, allowing the central bank to have more space before hitting the Zero Lower Bound. In fact, a 5% higher nominal interest rate would have allowed the FED to decrease the FFR about 5% more than was actually possible during the Great Recession and might have helped to avoid an encounter with the Zero Lower Bound (see Blanchard et al. (2010)). But this "more space" is payed by a long-run loss in TFP of about 0.05%, so increasing the inflation target permanently also

Figure 3.5: Impulse responses to a permanent 1 standard deviation increase in the inflation target as implied by the model. The dashed lines show the 90% credible intervals based on the highest posterior density interval (HPDI).



leads to a permanent loss in productivity. Summing up the results, it turns out that monetary policy shocks induce a slowly increasing long-run negative effect on TFP, maxing out at almost 0.02% below the TFP level without the shock. A temporary inflation target shock on the other side has an equally strong effect on TFP on impact, but compared to the monetary policy shock is recoverable in the medium run. Permanent inflation target shocks are not recoverable and lead to a long-run loss in TFP of about 0.05%. In the light of this, it becomes evident that a higher inflation target in order to reduce the probability of hitting the Zero Lower Bound induces long-run economic costs, as it leads to permanently lower productivity. In anticipation of hitting the Zero Lower Bound, the central bank could temporarily increase its inflation target in order to attain a higher nominal interest rate and then return back to its old target to avoid the long-run TFP loss, however the anticipation of a ZLB encounter itself might be difficult.

3.4 Conclusion

The present paper analyzes to what extent inflation target shocks affect long-term technological progress. A Newkeynesian model featuring endogenous technological progress and a central bank with a fluctuating inflation target is proposed and estimated using Bayesian methods. An inflation target shock incurs an increasing nominal interest rate alongside an increasing inflation rate. Under the assumed price rigidity, the firm markup decreases in the event of unexpected inflation. Firms are in Schumpeterian competition for the spot as incumbent in the market and the decreasing price markups decrease the incentive of the firms to compete in the innovation contest for being next period's incumbent. In consequence, technological progress declines and long-run TFP decreases. If the inflation target shock is permanent, the TFP effect is permanent as well, while productivity recovers in the long run, if the inflation target shock is only transitory. It turns out that a permanent inflation target shock that increases long-run average inflation about 5%, which would have allowed the U.S. FED to avoid the Zero Lower Bound during the Great Recession, leads to a permanent loss in TFP about 0.05%. However, if the inflation target shock is temporary, the negative effect on TFP can be recovered in the long run. As a secondary finding, the model supports the recent evidence of increasing nominal interest rates being connected with lower R&D activity and higher average inflation leading to lower long-run productivity. Inflation target shocks for this matter allow to bring together the findings of traditional monetary policy shocks that decrease inflation and have a negative effect on TFP and that higher inflation is associated with subsequently lower economic growth: Monetary policy shocks are only short-run events, if the central bank deviates from its policy rule for a longer period of time, it has to have changed its policy target. An inflation target shock on the other hand induces an increase in the nominal interest rate like a monetary policy shock, but in contrast leads to persistently higher inflation and has a negative effect on technological progress.

To sum up, defending against the Zero Lower Bound by permanently increasing the central bank's inflation target, thus average inflation and the average nominal interest rate, leads to long-run economic costs in the form of a permanent loss in TFP. These costs can only be avoided, if the encounter with the Zero Lower Bound is predicted and the inflation target can be set higher only temporary. As predicting an encounter with the Zero Lower Bound is quite hard in practice, it is unlikely that one can rely on temporary inflation target shocks as a viable instrument, thus increasing the inflation target permanently and incurring a long-run TFP loss seems to be inevitable if one wants to hedge against an encounter with the Zero Lower Bound. In the light of the present paper's findings, the discussion about the desirability of a higher average inflation needs to include a long-run perspective alongside the short-run analysis, if the full economic cost are to be considered.

Furthermore, the present paper supports the recent evidence concerning longer-run consequences of monetary policy, which challenges the traditional assumption of long-run neutrality of monetary policy. The further investigation of the longer-run effects of monetary policy is something future research definitely needs to address.

3.5 Appendix: Further derivations for section 3.2

3.5.1 Detrended form of the model

The model has a unique and stable steady state in detrended form. The TFP level can be decomposed into a trend and cyclical component. The trend component is $q^t_{t-1} = \lambda^{A_{t-1}}$ and thus trend growth is biven by $g^{qt}_{t-1} \approx \ln(q^t_{t-1}) - \ln(q^t_{t-2}) = \ln(\lambda)\Delta^A_{t-1}$. The variables growing on the balanced growth path are X_t, p^R_t, $p^{\mathcal{U}}_t$, Υ_t, p^A_t, Y_t, $\mathcal{M}_t$, W_t and C_t, while the remaining variables are stationary. Dividing all growing variables by the trend component yields the detrended form of the model (all variables in detrended form are denoted by a tilde):

$$r_t = \bar{r}\left(\frac{\pi_t}{\pi^T_t}\right)^{\omega^\pi}\left(\frac{n_t}{\bar{n}}\right)^{\omega^n} exp(\varepsilon^r_t) \tag{3.64}$$

$$\pi^T_t = \bar{\pi^T} exp(f_t) \tag{3.65}$$

$$f_t = \rho^f f_{t-1} + \varepsilon^\pi_t \tag{3.66}$$

$$R_t = \chi\left(\frac{\tilde{X}_t}{exp(e_t)}\right)^{1-\kappa}\mathcal{U}^{\mu_x}_{t-1} \tag{3.67}$$

$$\frac{\tilde{p^R}_t}{exp(e_t)}\chi(1-\kappa)\mathcal{U}^{\mu_x}_{t-1} = \left(\frac{\tilde{X}_t}{exp(e_t)}\right)^{\kappa} \tag{3.68}$$

$$\mathcal{U}_t = (1-\delta^{\mathcal{U}})\mathcal{U}_{t-1} + R_t - \Delta^A_t \tag{3.69}$$

$$\tilde{p^R}_t = E_t\Lambda_{t,t+1}\tilde{p^{\mathcal{U}}}_{t+1}(1+g^{qt}_t) \tag{3.70}$$

$$\Delta^A_t = \left(\frac{\tilde{\Upsilon}_t}{exp(e_t)}\right)^{1-\xi}\mathcal{U}_{t-1} \tag{3.71}$$

$$\frac{\tilde{p^A}_t}{exp(e_t)}(1-\xi)\mathcal{U}_{t-1} = \left(\frac{\tilde{\Upsilon}_t}{exp(e_t)}\right)^{\xi} \tag{3.72}$$

$$\tilde{p^A}_t\left(\frac{\tilde{\Upsilon}_t}{exp(e_t)}\right)^{1-\xi} = \tilde{p^{\mathcal{U}}}_t \tag{3.73}$$

$$\tilde{Y}_t = exp(e_t)n_t \tag{3.74}$$

$$e_t = \rho^e e_{t-1} + \varepsilon^q_t \tag{3.75}$$

$$\tilde{\mathcal{M}}_t = \tilde{Y}_t - \tilde{W}_t n_t - \frac{\theta}{2}\left[\frac{1+\pi_t}{(1+\pi_t^T)^\iota(1+\pi_{t-1})^{1-\iota}} - 1\right]^2 \tilde{Y}_t \tag{3.76}$$

$$\tilde{p^A}_t \Delta_t^A = E_t \Lambda_{t,t+1} \tilde{\mathcal{M}}_{t+1}(1+g_t^{qt}) \tag{3.77}$$

$$g_t^y \approx g_{t-1}^{qt} + e_t - e_{t-1} + \ln(n_t) - \ln(n_{t-1}) \tag{3.78}$$

$$\left[\frac{1+\pi_t}{(1+\pi_t^T)^\iota(1+\pi_{t-1})^{1-\iota}} - 1\right]\frac{1+\pi_t}{(1+\pi_t^T)^\iota(1+\pi_{t-1})^{1-\iota}} = \frac{\varepsilon-1}{\theta}\left[\frac{\varepsilon}{\varepsilon-1}\frac{\tilde{W}_t}{exp(e_t)} - 1\right]$$
$$+ E_t\Lambda_{t,t+1}\left[\frac{1+\pi_{t+1}}{(1+\pi_{t+1}^T)^\iota(1+\pi_t)^{1-\iota}} - 1\right](1+g_{t+1}^y)\frac{1+\pi_{t+1}}{(1+\pi_{t+1}^T)^\iota(1+\pi_t)^{1-\iota}} \tag{3.79}$$

$$n_t^\varphi = \tilde{W}_t \tilde{C}_t^{-1} \tag{3.80}$$

$$\tilde{C}_t^{-1} = \beta\frac{exp(d_{t+1})}{exp(d_t)}\frac{1+r_t}{1+g_t^{qt}}\tilde{C}_{t+1}^{-1} \tag{3.81}$$

$$d_t = \rho^\beta d_{t-1} + \varepsilon_t^\beta \tag{3.82}$$

$$\Lambda_{t,t+1} = \frac{1}{1+r_t} \tag{3.83}$$

$$\tilde{Y}_t = \tilde{C}_t \tag{3.84}$$

3.5.2 Steady state of the detrended form model

Dropping the time indices in the detrended form model then yields the steady state (asterisks denote steady state values), which reads

$$\pi^* = \pi^{T*} \tag{3.85}$$

$$\pi^{T*} = \bar{\pi^T} \tag{3.86}$$

$$R^* = \chi(\tilde{X}^*)^{1-\kappa}(\mathcal{U}^*)^{\mu_x} \tag{3.87}$$

$$p^{\tilde{R}*}\chi(1-\kappa)(\mathcal{U}^*)^{\mu_x} = (\tilde{X}^*)^\kappa \tag{3.88}$$

$$\delta^{\mathcal{U}}\mathcal{U}^* = R^* - \Delta^{A*} \tag{3.89}$$

$$p^{\tilde{R}*} = \frac{1+g^{qt*}}{1+r^*}p^{\tilde{\mathcal{U}}*} \tag{3.90}$$

$$\Delta^{A*} = (\tilde{\Upsilon}^*)^{1-\xi}\mathcal{U}^* \tag{3.91}$$

$$p^{\tilde{A}*}(1-\xi)\mathcal{U}^* = (\tilde{\Upsilon}^*)^\xi \tag{3.92}$$

$$p^{\tilde{A}*}(\tilde{\Upsilon}^*)^{1-\xi} = p^{\tilde{\mathcal{U}}*} \tag{3.93}$$

$$\tilde{Y}^* = n^* \tag{3.94}$$

$$\tilde{\mathcal{M}}^* = \tilde{Y}^* - \tilde{W}^* n^* - \frac{\theta}{2}\left[\frac{1+\pi^*}{1+\bar{\pi^T}*} - 1\right]^2 \tilde{Y}^* \tag{3.95}$$

$$p^{\tilde{A}*}\Delta^{A*} = \frac{1+g^{qt*}}{1+r^*}\tilde{\mathcal{M}}^* \tag{3.96}$$

$$g^{y*} = g^{qt*} \tag{3.97}$$

$$\begin{aligned} &\left[\frac{1+\pi^*}{1+\pi^{\bar{T}*}} - 1\right]\frac{1+\pi^*}{1+\pi^{\bar{T}*}} = \frac{\varepsilon-1}{\theta}\left[\frac{\varepsilon}{\varepsilon-1}\tilde{W}^* - 1\right] \\ &+ \frac{1+g^{y*}}{1+r^*}\left[\frac{1+\pi^*}{1+\pi^{\bar{T}*}} - 1\right]\frac{1+\pi^*}{1+\pi^{\bar{T}*}} \end{aligned} \tag{3.98}$$

$$(n^*)^{\varphi} = \tilde{W}^*(\tilde{C}^*)^{-1} \tag{3.99}$$

$$\beta = \frac{1+g^{qt*}}{1+r^*} \tag{3.100}$$

$$\tilde{Y}^* = \tilde{C}^* \tag{3.101}$$

$$g^{qt*} = \ln(\lambda)\Delta^{A*} \tag{3.102}$$

Under the calibrated and estimated parameter values from before, the model has 7 forward looking variables and there are 7 eigenvalues larger than 1 in modulus, so the Blanchard-Khan conditions are fulfilled and there exists a unique and stable steady state for the detrended form model.

3.5.3 Recalculation of TFP growth in contrast to Fernald (2012-2019)

The TFP growth series calculated by Fernald (2012-2019) is defined as the residual between output and input growth. He assumes a production function with capital and labor augmenting technological progress of the form (variable definitions as before)

$$Y_t = q_t^{Fernald} K_{t-1}^{\alpha} n_t^{1-\alpha} \tag{3.103}$$

and by taking logs and first differences

$$\begin{aligned} \ln(Y_t)-\ln(Y_{t-1}) &= \alpha\left(\ln(K_{t-1}) - \ln(K_{t-2})\right)+(1-\alpha)\left(\ln(n_t) - \ln(n_{t-1})\right)+g_t^{q,Fernald} \\ \Leftrightarrow g_t^{q,Fernald} &= \ln(Y_t)-\ln(Y_{t-1})-\alpha\left(\ln(K_{t-1}) - \ln(K_{t-2})\right)-(1-\alpha)\left(\ln(n_t) - \ln(n_{t-1})\right). \end{aligned} \tag{3.104}$$

However, the model in this paper assumes purely labor augmenting technological progress (as there is no capital), which can be seen by inserting the intermediate goods production function (3.18) in the final goods production function (3.15)

$$Y_t = \left(\int_0^1 (q_{i,t}n_{i,t})^{\frac{\varepsilon-1}{\varepsilon}}\, di\right)^{\frac{\varepsilon}{\varepsilon-1}}. \tag{3.105}$$

To make the TFP growth rate provided by Fernald (2012-2019) consistent with the one defined within the model, it has to be adjusted accordingly. Reformulating the production function of Fernald (2012-2019) such that productivity is purely labor augmenting yields

$$Y_t = K_{t-1}^{\alpha} \left(q_t n_t\right)^{1-\alpha}, \tag{3.106}$$

thus by taking logs and first differences

$$\begin{aligned} \ln(Y_t) - \ln(Y_{t-1}) &= \alpha \left(\ln(K_{t-1}) - \ln(K_{t-2})\right) + (1-\alpha)\left(\ln(n_t) - \ln(n_{t-1}) + g_t^q\right) \\ \Leftrightarrow (1-\alpha) g_t^q &= \ln(Y_t) - \ln(Y_{t-1}) - \alpha \left(\ln(K_{t-1}) - \ln(K_{t-2})\right) - (1-\alpha)\left(\ln(n_t) - \ln(n_{t-1})\right) \end{aligned} \tag{3.107}$$

and thus

$$g_t^q = \frac{1}{1-\alpha} g_t^{q,Fernald}. \tag{3.108}$$

In order to make the observed TFP series fitting to the model implied TFP series, the data series of Fernald (2012-2019) is multiplied with $\frac{1}{1-\alpha}$. In fact, Fernald (2012-2019) also provides data on the capital share α_t for each observation period, which is used to recalculate the TFP series. The results in the main paper, however, are not sensitive to the recalculation of TFP, thus it is only performed for consistency between model and data.

3.6 Appendix: Computational details

There exists a closed form solution for the system of steady state equations, which is passed on to the Dynare steady state file to ease the computational burden and make the analysis less dependent on initial values for numerical solver routines. The solution for the steady state is given by

$$\tilde{W}^* = \frac{\varepsilon - 1}{\varepsilon} \tag{3.109}$$

$$\tilde{Y}^* = \left(\frac{\varepsilon - 1}{\varepsilon}\right)^{\frac{1}{1+\varphi}} \tag{3.110}$$

$$n^* = \tilde{Y}^* \tag{3.111}$$

$$\tilde{C}^* = \tilde{Y}^* \tag{3.112}$$

$$\tilde{\mathcal{M}}^* = \frac{1}{\varepsilon}\tilde{Y}^* \tag{3.113}$$

$$\tilde{\Upsilon}^* = (1-\xi)\beta\tilde{\mathcal{M}}^* \tag{3.114}$$

$$\tilde{X}^* = \left(\delta^{\mathcal{U}} + \gamma(\tilde{\Upsilon}^*)^{1-\xi}\right) \beta^2 \tilde{\mathcal{M}}^*(1-\kappa) \tag{3.115}$$

$$\mathcal{U}^* = \left(\frac{(\tilde{X}^*)^{\kappa}}{\beta^2 \tilde{\mathcal{M}}^* \chi(1-\kappa)} \right)^{\frac{1}{\mu_x - 1}} \tag{3.116}$$

$$\Delta^{A*} = \gamma(\tilde{\Upsilon}^*)^{1-\xi}\mathcal{U}^* \tag{3.117}$$

$$g^{qt*} = \ln(\lambda)\Delta^{A*} \tag{3.118}$$

$$g^{y*} = g^{qt*} \tag{3.119}$$

$$R^* = \chi(\tilde{X}^*)^{1-\kappa}(\mathcal{U}^*)^{\mu_x} \tag{3.120}$$

$$r^* = \left(\frac{1+g^{qt*}}{\beta}\right) - 1 \tag{3.121}$$

$$\Lambda^* = \frac{1}{1+r^*} \tag{3.122}$$

$$p^{\tilde{\mathcal{U}}*} = \frac{\tilde{\Upsilon}^*}{(1-\xi)\mathcal{U}^*} \tag{3.123}$$

$$p^{\tilde{R}*} = \beta p^{\tilde{\mathcal{U}}*} \tag{3.124}$$

$$p^{\tilde{A}*} = \frac{(\tilde{\Upsilon}^*)^{\xi}}{(1-\xi)\gamma\mathcal{U}^*}. \tag{3.125}$$

For the Bayesian estimation the Monte-Carlo based optimization routine (mode_compute = 6 in Adjemian et al. (2011)) is used.

3.7 Appendix: Historical importance of inflation target shocks concerning technological progress

In this section the historical importance of inflation target shocks concerning technological progress is analyzed. Table 3.4 summarizes the variance decomposition for the trend TFP growth g^{qt}, stock of unadopted ideas $\mathcal{U}$, invention of new ideas R and adoption effort Υ with respect to the four structural shocks. As it can be

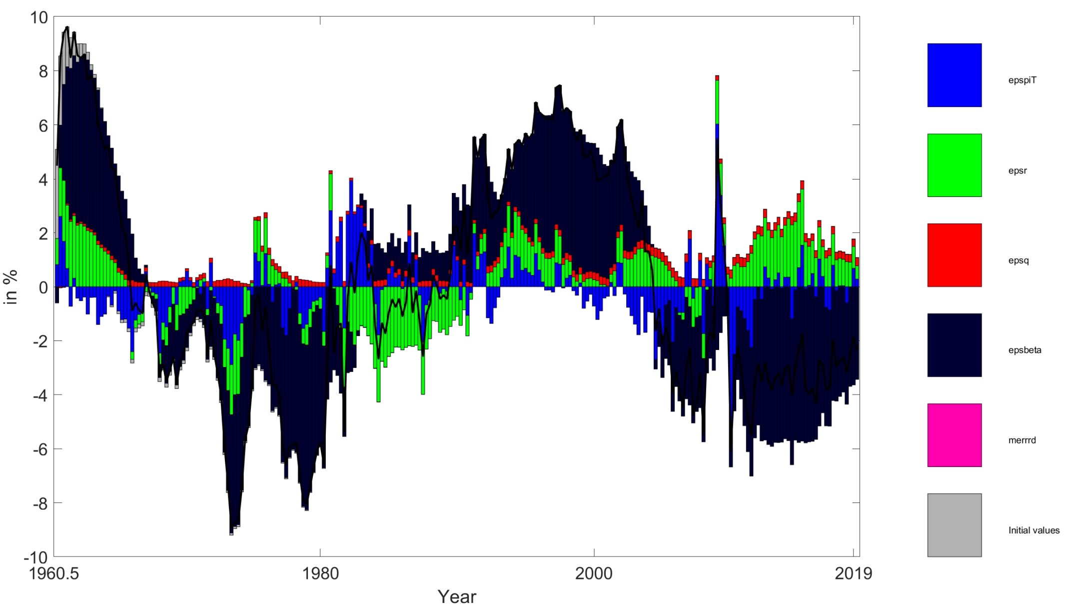
Table 3.4: Variance decomposition (in %)

Variable	ε^{π}	ε^{r}	ε^{q}	ε^{β}
g^{qt}	50.50	9.21	0.20	40.09
$\mathcal{U}$	22.80	12.31	0.52	64.36
R	45.31	20.44	0.15	34.10
$\tilde{\Upsilon}$	1.41	0.25	97.78	0.56

seen, inflation target shocks account for about five times more of the variance of trend TFP growth than monetary policy shocks do. It becomes evident that most of the effect on trend TFP growth from inflation target shocks works through the production and accumulation of unadopted ideas, as it explains over 45% of the variance in the production of new ideas R and about 20% of the variance of the stock of unadopted ideas $\mathcal{U}$, but are negligible concerning the technology adoption effort Υ. Of all the four structural shocks, inflation target shocks explain, with more than 50%, the most about the variance in trend TFP growth with the runner up being the consumer preference shock with about 40%. Monetary policy shocks explain the third most with slightly below 10% of the variance, while the influence of TFP shocks is negligible concerning the variance in endogenous technological progress.

Now the question is, if there are periods of time that are main drivers for the high share of variance in endogenous TFP explained by the inflation target shock. Figure 3.6 shows the historical shock decomposition of the endogenous part of TFP growth (g^{gt} in the model) with respect to the 4 structural shocks. As it becomes

Figure 3.6: Historical shock decomposition of the endogenous part of TFP growth (g^{gt} in the model). The solid line gives the historical simulation of the endogenous TFP growth series, while the bars show the influence of the individual shocks at each point in time.



evident there are no outstandingly influential periods of time that drive the results of the variance decomposition regarding inflation target shocks. Of course there is a negative influence of the inflation target shock during the two oil price crises in the 1970s, when the FED did not answer the high inflation during this time with an accordingly even higher interest rate, and a positive influence on endogenous TFP growth after 1980, when the FED performed a strong anti-inflationary policy. During the onset of the Great Recession, there is a short but strong positive effect of an inflation target shock, as the central bank encountered the Zero Lower Bound and was not able to protect its old inflation target. But there is no period of time that seems to solely drive the simulated inflation target shock and clouds the results of the above analysis. If there is one shock that is at some times much more influential than at other times, its the consumer preference shock that had a huge positive spike during the 1960s and 1990s and a similarly large negative spike during the two oil price crises and the aftermath of the Great Recession. But as the business cycle literature often times believes the business cycle to be mainly demand driven (see Beaudry and Portier (2014)), this might not be a very surprising result.

3.8 Appendix: Omitting the oil price crises

One could argue that the observations before the 1980s should be omitted from the estimation, as the two oil price crises during the 1970s might be influential for the estimation results. Table 3.5 compares the estimated posterior modes concerning

Table 3.5: Comparing the posterior modes for the 1960-2019 and the 1983-2019 observation period

Parameter	Mode 1960-2019	Mode 1983-2019
ω^{π}	0.2922	0.3734
ι	0.2731	0.3242
ε	5.5007	5.6448
θ	124.8911	111.7147
κ	0.2880	0.3443
μ_x	0.7439	0.7604
ξ	0.0314	0.0479
$\delta^{\mathcal{U}}$	0.0447	0.0763
ρ^e	0.9966	0.9904
ρ^f	0.9706	0.9540
ρ^{β}	0.0249	0.069
s.e. ε^{π}	1.2808	1.1708
s.e. ε^{r}	1.0928	1.0619
s.e. ε^{q}	0.0115	0.0096
s.e. ε^{β}	0.0797	0.056
s.e. γ	0.0022	0.0011

all parameters for the 1960-2019 and 1983-2019 observation period. As it becomes evident, the estimation results do not differ much and are robust to the omission of the 1960-1983 observations.

3.9 Appendix: Business cycle effects of inflation target and monetary policy shocks

This section is intended to have a look on the classical business cycle effects of inflation target and monetary policy shocks, in order to evaluate also the short-run properties of the model proposed in the main body of the paper. In the business cycle literature, it is common to detrend variables and look at the fluctuations in the "cyclical" component, where the term "cyclical" refers to high frequency fluctuations. In accordance to this approach, this section looks at the fluctuations in detrended output $\tilde{Y}$, detrended consumption $\tilde{C}$, detrended real wages $\tilde{W}$ and the real interest rate r. This section is intended as a plausibility check for the model implications.

Table 3.6 summarizes the variance decomposition for the variables mentioned above regarding the four structural shocks considered in the model. The inflation target

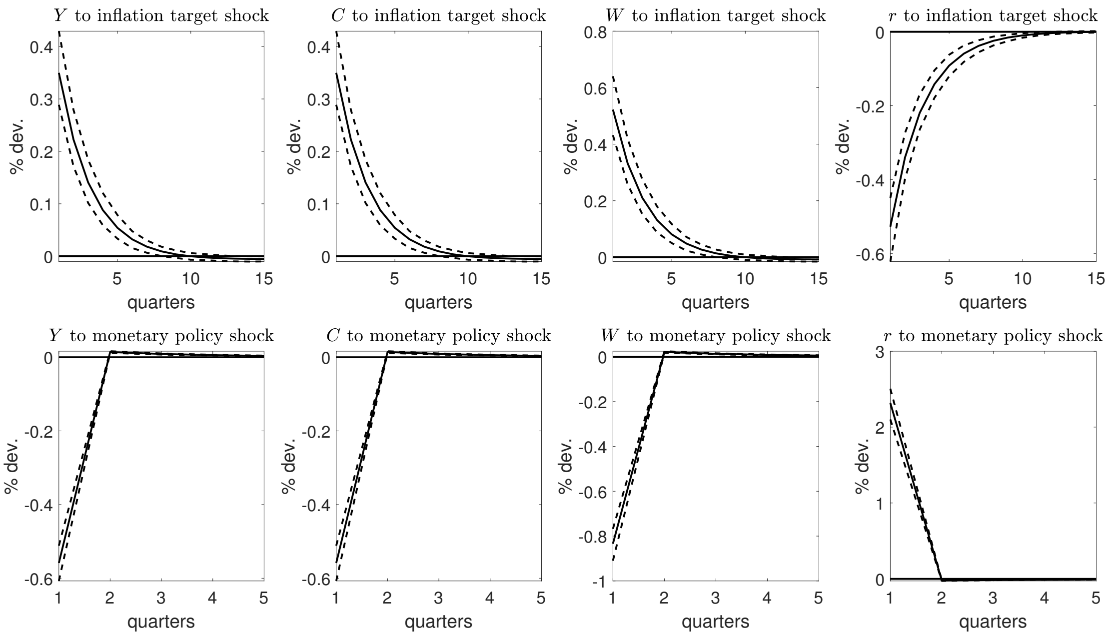
Table 3.6: Variance decomposition (in %)

Variable	ε^{π}	ε^{r}	ε^{q}	ε^{β}
$\tilde{Y}$	0.09	0.14	74.49	25.28
$\tilde{C}$	0.09	0.14	74.49	25.28
$\tilde{W}$	0.16	0.24	56.46	43.14
r	7.64	82.50	0.64	9.23

and monetary policy shocks do not seem to play an important role in explaining high frequency fluctuations in output, consumption and real wages, in fact both explain much less than 1% of the variance in those three variables. High frequency fluctuations in output, consumption and real wages can almost single-handedly be explained by aggregate TFP shocks, which account for about three quarters of the variance in these variables, and consumer preference shocks, which account for the remaining quarter of the observed variance in output, consumption and real wages. However, regarding the real interest rate, it becomes evident that TFP shocks explain less than 1% of the variance, while consumer preference shocks explain only about 10%. Concerning the shocks originating from the central bank sector, it turns out that the majority of fluctuations are accounted for by monetary policy shocks, which explain over 80% of the variance in the real interest rate, while inflation target shocks are relatively unimportant, explaining less than 8% of the variance in the real interest rate.

Figure 3.7 shows the impulse responses of output, consumption, real wages and the real interest rate to an inflation target and monetary policy shock of size one standard deviation (which translates into a change of about 5 percentage points in the inflation target and a change of 0.5 percentage points in the real interest rate respectively). As it can be seen, the inflation target shock leads to a decrease in the

Figure 3.7: Impulse responses of detrended output, detrended consumption, detrended wages and the real interest rate to a 1 standard deviation inflation target and monetary policy shock as implied by the estimated model. The dashed lines give the 90% credible interval based on the highest posterior density interval (HPDI).



real interest rate of about 0.5% on impact. In the main body of this paper, it was shown that the inflation target shock leads to an increase in the nominal interest rate, but as the simultaneous increase in inflation is even stronger, the real interest rate declines. The return back to the steady state is relatively quick, as after about 3 years the real interest rate is back at its steady state value. The decline in the real interest rate leads to an increase in output and consumption, which both increase about 0.35% on impact. The increase in production at a predetermined productivity level on impact leads to an increase in employment and, in consequence, to an increase in the real wage, which increases about 0.5% on impact of the inflation target shock. As the real interest rate, also output, consumption and real wages return back to the steady state in relatively short time, in this case even less than 3 years. Regarding the monetary policy shock, it leads to an increase in the real interest rate by over 2% on impact. Here, the difference between inflation target and monetary policy shocks becomes evident again, as both lead to an increase in the nominal interest rate, but only the monetary policy shock leads to an increase in the real interest rate as well. The increase in the real interest rate leads to a decline in consumption and output of about nearly 0.6%, while real wages decline by about 0.8%. After the initial decline in output, consumption and real wages, there is a short period of a small positive effect on these variables that hails back to the higher incentive to save and increase future consumption after the real interest rate increases. However, by definition the shock effect of the monetary policy shock has very little persistence and completely vanishes after at least 5 quarters.

In summary, it becomes evident from the analysis above that inflation target shocks play a minor role in explaining the variance in detrended output, detrended consumption, detrended real wages and the real interest rate and have only an effect with low persistence on these variables. The finding of the main body of this paper and the appendix section about the historical importance of inflation target shocks was that inflation target shocks play a much bigger role concerning longer-run fluctuations in technological progress. So it seems that inflation target shocks are nothing that really concerns the high frequency business cycle, but rather the medium-run cycle.

4 Monetary policy and the stock market - A partly-recursive SVAR estimator[1]

4.1 Introduction

Simultaneously identifying monetary policy and stock market shocks in an SVAR is an ongoing challenge for econometricians. As usual, concluding the structural shocks from the reduced form errors is not possible without imposing additional identifying restrictions, so identifying both shocks mentioned above requires to impose an a priori structure. Most of the literature covers one of two extreme cases:

I) Identifying all shocks based on ex ante restrictions concerning the short- or long-run impact of the structural shocks on the observed variables, or

II) data-driven approaches without ex ante restrictions on the short- or long-term shock effect, but based on heteroskedastic or non-Gaussian shocks, who are able to provide further information regarding the structural shocks based on moment conditions that can be used for identification.

We argue that none of the two extreme cases is suited for the application at hand. In particular, we show that commonly used short- and long-run restrictions on the interaction of monetary policy and the stock market are questionable and are essentially equivalent with ex ante choosing the model one does believe in without letting the data decide, which model fits best. However, also purely data-driven estimators do not yield conclusive insights concerning the interaction of both variables, since these estimators depend on latent, volatile, or hardly observable features, which results in a poor small sample performance of the estimator. This problem gets more and more serious, the more variables are controlled for in the SVAR, which makes purely data-driven identification approaches less helpful in larger SVARs.

The estimator proposed in this study combines the traditional identification approach based on short-run zero restrictions in a recursive ordering with the more recently developed data-driven approach based on non-Gaussianity. Our estimator allows the researcher to rely on recursiveness restrictions if possible and to be agnostic on the interaction of the variables and rely on data-driven estimates when

[1]joint work with Sascha A. Keweloh, a slightly different version appeared as Keweloh, S.A. and Andre Seepe (2020), *Monetary policy and the stock market - A partly-recursive SVAR estimator*, SFB 823 Discussion Paper series No. 32/2020, http://dx.doi.org/10.17877/DE290R-21722

necessary. The estimator is then applied to analyze the interaction of monetary policy and the stock market. We find no strong evidence for the usage of common short- and long-run restrictions and demonstrate that a purely data-driven estimator leads to imprecise estimates, which barely allow any conclusions about the effect of monetary policy shocks on the stock market and stock market shocks on monetary policy.

In the literature, the interaction of monetary policy and the stock market has been estimated based on short-run restrictions (see e.g. Laopodis (2013)) and on long-run restrictions (see Bjørnland and Leitemo (2009) or Kontonikas and Zekaite (2018)). The estimation based on short-run restrictions in Laopodis (2013) yields evidence that real stock prices are persistently negative after a tightening of monetary policy, which is at odds with the long-run restrictions used in Bjørnland and Leitemo (2009). However, the estimation based on long-run restrictions by Bjørnland and Leitemo (2009) suggests that any zero restriction on the interaction of monetary policy and the stock market is incorrect as well and is thus at odds with the short-run restrictions used in Laopodis (2013). Therefore, the results from the restriction based approaches contradict each other. We argue that neither the short- nor the long-run restrictions are plausible and thus an approach that abstains from such is a better choice for the matter at hand. In particular, stock market shocks can contain news about future business cycle fluctuations (see e.g. Beaudry and Portier (2006)) and assuming that the central bank does not react simultaneously, which means within 3 months for quarterly data, to these shocks is debatable. Moreover, recent studies (see Moran and Queralto (2018), Bianchi et al. (2019) and Jordà et al. (2020)) find evidence against the long-run neutrality of monetary policy, which casts doubt on any long-run restrictions used to identify monetary policy shocks as in Bjørnland and Leitemo (2009) or Kontonikas and Zekaite (2018).

Due to the unavailability of short- and long-run restrictions, several authors use data-driven approaches to estimate the interaction of monetary policy and the stock market (see Lanne et al. (2017) or Lütkepohl and Netšunajev (2017)). These approaches do not require any ex ante restrictions on the interaction of the variables, but instead exploit a structure imposed on the statistical properties of the structural shocks. Lütkepohl and Netšunajev (2017) estimate the interaction of monetary policy and the stock market based on time-varying volatility and find a negative impact of a tightening of monetary policy on stock prices. However, the authors are unable to clearly label a stock market shock. Moreover, a tightening of monetary policy appears to have an, at least from standard theory, unexpected initial positive impact on output and inflation and, therefore, even the labeling of the monetary policy shock is debatable. Lanne et al. (2017) estimate an SVAR based on non-Gaussianity of the structural shocks and find that a tightening of monetary policy has an immediate negative impact on the stock market. However, they are also unable to label any other shock besides the monetary policy shock and in particularly are not able to label a stock market shock.

In the present paper, we argue that neither the traditional short- or long-run restriction based approaches, nor the more recently developed, purely data-driven approaches yield conclusive insights into the interaction of monetary policy and the stock market. The restriction based approaches fail due to the unavailability of sufficiently many short- or long-run restrictions and the data-driven approaches fail, since they impose such little structure that finite sample estimates become highly volatile, up to the point that it becomes difficult to even label the shocks.

From our point of view, the key to gain insight into the interaction of monetary policy and the stock market is a combination of the traditional restriction based and the more recently developed data-driven approach. The estimator proposed in this study allows to divide the variables of the SVAR into a first block of recursively ordered variables, so we impose short-run zero restrictions on the contemporaneous shock effects concerning the variables ordered above the respective row of the structural shock, and a second block of non-recursive variables, where we impose no short- or long-run restrictions, but rely only on the information retrieved from moments beyond the variance of non-Gaussian shocks for identification. Most importantly, here only the non-recursive block relies on data-driven estimates based on non-Gaussian and independent shocks. The more recursiveness restrictions the researcher applies, the less the estimator depends on moments beyond the variance and the better the small sample performance of the SVAR estimator. In a Monte Carlo simulation, we show how the performance of a purely data-driven estimator based on non-Gaussianity deteriorates with a decreasing sample size and an increasing model size. However, the simulation also shows that exploiting the partly-recursive order can stop the performance decline. Therefore, the estimator proposed in this study allows the researcher to rely on an arbitrary number of recursiveness restrictions, which reduces the dependence of the estimator on moments beyond the variance and thereby increases the finite sample performance of the estimator, which allows for more conclusive results and an easier labeling of the structural shocks.

In our application the variables output, investment and inflation are assumed to be rigid in the short run and are restricted such that they cannot respond to stock market and monetary policy shocks within the same quarter. However, the Federal Funds Rate and stock returns remain unrestricted and can simultaneously respond to all shocks. In consequence, we have a block of three variables that are recursively ordered and two variables that are identified based on moments beyond the variance. We apply the proposed partly-recursive estimator and find a contemporaneous contractionary response of the Federal Funds Rate to positive stock market shocks and an immediate negative stock return response to contractionary monetary policy shocks. Moreover, we find no strong evidence against monetary policy having a long-run effect on stock prices, like in the recent papers of Moran and Queralto (2018) or Bianchi et al. (2019). Additionally, as a robustness check we estimate an unrestricted SVAR solely based on independent and non-Gaussian shocks. Overall, the unrestricted estimation confirms the results of our partly-recursive estimation, especially the applicability of the short-run zero restrictions for the recursive block. However, the confidence intervals are larger and it becomes increasingly difficult to explain the estimated interaction of stock prices and interest rates. The application illustrates that the partly-recursive, partly non-Gaussian identification scheme introduced in the present study serves as a helpful addition to the econometrician's tool box when faced with situations, where only a few restrictions on the interaction of the variables are available.

The remainder of this article is structured as follows: Section 4.2 shows that commonly used identification schemes in the related literature come with caveats that render them not applicable to analyze the interaction of monetary policy and the stock market. Section 4.3 derives our estimator for partly-recursive, partly non-Gaussian SVAR models and contains a Monte-Carlo study illustrating how exploiting the partly-recursive order increases the finite sample performance of the estimator. In section 4.4 we use the proposed partly-recursive, partly non-Gaussian SVAR estimator to analyze the interaction of the stock market and monetary policy. Section 4.5 concludes.

4.2 Monetary policy and the stock market

4.2.1 The unavailability of common identifying restrictions

In this section, we use a simple macroeconomic asset pricing model to illustrate that there is no indisputable answer about the short- and long-run effect of stock market and monetary policy shocks. We keep the model intentionally simple to show that only a small deviation in basic assumptions can make a big difference for the short- and long-run effect of monetary policy and stock market shocks. In particular, we show that imposing a long-run restriction on the effect of monetary policy shocks on stock prices, as frequently done by the literature (see Bjørnland and Leitemo (2009) or Kontonikas and Zekaite (2018)), essentially boils down to choosing the model one believes in ex ante without letting the data have a say about which model world fits best.

Consider that households can save by buying firm stocks of firm i at price $v_{i,t}$, which yield dividend $d_{i,t+1}$ and can be sold in the next period at price $v_{i,t+1}$, or by a non-contingent bond b_t^f yielding a guaranteed real interest at rate r_t. The Euler equations for the households then read

$$\frac{u'(c_t)}{u'(c_{t+1})} = \beta(1 + r_t) \tag{4.1}$$

$$\frac{u'(c_t)}{u'(c_{t+1})} = \beta E_t \frac{v_{i,t+1} + d_{i,t+1}}{v_{i,t}}, \tag{4.2}$$

with $u'(c_t)$ the marginal utility of consumption with the usual properties $u'(c_t) > 0$, $u''(c_t) < 0$ and β the household discount factor. Thus, the no-arbitrage condition is

$$1 + r_t = E_t \frac{v_{i,t+1} + d_{i,t+1}}{v_{i,t}}. \tag{4.3}$$

From this, one can acquire the familiar central asset pricing equation of the form

$$v_{i,t} = E_t \sum_{s=1}^{\infty} \frac{d_{i,t+s}}{\prod_{j=1}^{s}(1 + r_{t+j-1})}, \tag{4.4}$$

so the current stock price is the expected discounted sum of future dividends.

On the firm side, assume a continuum of infinitely small firms with mass 1 that try to maximize the dividends they are paying out to the households, where dividends of firm i are given by

$$d_{i,t+s} = y_{i,t+s} - j_{i,t+s} + b^f_{i,t+1+s} - (1 + r_{t+s-1})b^f_{i,t+s} - \bar{w}\bar{n}, \tag{4.5}$$

where $y_{i,t}$ is output, $j_{i,t}$ investment in the physical capital stock, $b^f_{i,t}$ is a loan of the firm (where $\int_0^1 b^f_{i,t} di = b^f_t$), $\bar{w}$ the constant real wage and $\bar{n}$ labor input, also assumed constant for simplicity. We assume further an accumulation of physical capital $k_{i,t}$ of the form

$$k_{i,t+1} = (1-\delta)k_{i,t} + j_{i,t}, \quad \delta \in (0,1), \tag{4.6}$$

with δ the depreciation rate of physical capital. The production function reads

$$y_{i,t} = Ak_{i,t}^{\alpha}(Z_t\bar{n})^{1-\alpha}, \quad \alpha \in (0,1), \tag{4.7}$$

with A an exogenous scaling factor, $\bar{n}$ for simplicity constant labor input and Z_t an aggregate productivity factor exogenous to the individual firm, which will be discussed in detail later on. Consequently, the firm maximization problem reads

$$\max_{\left\{k_{i,t+1+s}, b^f_{i,t+s}\right\}} \sum_{s=0}^{\infty} E_t \Lambda_{t+s} d_{i,t+s}, \tag{4.8}$$

with Λ_t the firm's discount factor and subject to (4.6)-(4.7). The optimality conditions yield the common interest rate parity condition of the form

$$E_t A\alpha k_{i,t+1}^{\alpha-1}(Z_{t+1}\bar{n})^{1-\alpha} + (1-\delta) = 1 + r_t, \tag{4.9}$$

which says that in the equilibrium the interest rate on loans and the return on capital investment will coincide. Now inserting (4.5)-(4.7) into (4.4) yields

$$v_{i,t} = E_t \sum_{s=1}^{\infty} \frac{\begin{aligned} Ak_{i,t+s}^{\alpha}(Z_{t+s}\bar{n})^{1-\alpha} - k_{i,t+s+1} + (1-\delta)k_{i,t+s} + b^f_{i,t+1+s} \\ - (1+r_{t+s-1})b^f_{i,t+s} - \bar{w}\bar{n} \end{aligned}}{\prod_{j=1}^{s}(1+r_{t+j-1})}. \tag{4.10}$$

Imposing the no bubbles limiting condition $\lim_{T\to\infty} b_T = 0$ then leads to the stream of future loans dropping out from the asset pricing equation, as dividends cannot be debt-financed indefinitely. As becomes evident, the dynamics of the numerator are then entirely driven by the evolution of capital. Using equation (4.9) then allows to find the evolution of capital as

$$k_{i,t+1} = E_t\left[\left(\frac{\alpha A}{r_t+\delta}\right)^{\frac{1}{1-\alpha}} \bar{n} Z_{t+1}\right]. \tag{4.11}$$

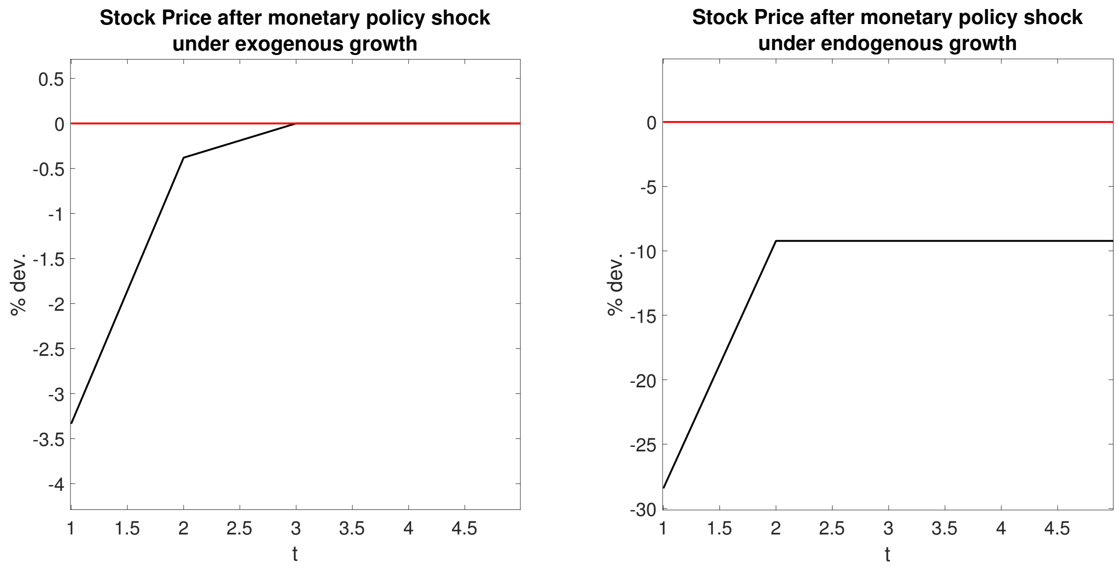
Now consider that the real interest rate increases once exogenously, which is what happens in standard macroeconomic models after a monetary policy shock under price rigidity, such that $r'_t > r^*_t$ and for the rest of the time $r'_{t+s} = r^*_{t+s}, \forall s > 0$ (primes denote variables after the shock, asterisks variables without the shock). The resulting response of dividends and thus ultimately stock prices now crucially depends on what we assume about the productivity factor Z_t:

1.) Exogenous growth: Assume a neoclassical growth model with decreasing marginal returns to capital, so $Z_t = exp(gt)Z_0$ is some variable growing at the exogenous rate g.

2.) Endogenous growth: Assume an endogenous growth model, for instance a standard learning-by-doing technology with $Z_t = \int_0^1 k_{i,t-1} di = K_{t-1}$.

Figure 4.1 shows the effect of an exogenous real interest rate increase about 1 percentage point on stock prices for the exogenous and endogenous growth model[2]. Assuming sticky prices, thus nominal and real variables move in the same direction

Figure 4.1: Simulated response of real stock prices to a one-time exogenous real interest rate increase of about one percentage point as induced by a monetary policy shock under price rigidity. The left-hand side shows the stock price reaction under exogenous growth (case 1.)), the right hand side under endogenous growth (case 2.))



in the short run, we can interpret the exogenous real interest rate increase as equivalent to a monetary policy shock. Both models imply an immediate reaction

[2]For simplicity we assume $\bar{n} = 1$, the initial debt $b_t^f = 0$, $\bar{w} = 0$. As $\bar{w}$ and $\bar{n}$ are constant, while b_t^f is a predetermined initial debt level, their calibration is qualitatively unimportant for the impulse responses, thus here without loss of generality. We use a standard calibration of $\alpha = \frac{1}{3}$, $\delta = 0.1$ and set $A = 0.46$ to ensure a long-run output growth rate of about 3%.

of stock prices to the monetary policy shock. However, in the exogenous growth model with decreasing returns to capital, stock prices revert back to their long-run level, while under endogenous growth with the learning-by-doing technology, the decrease in stock prices is permanent. This is because in the first case the lower capital stock implies a higher marginal return of capital in the future, which drives back capital to its old steady state, while in the second case it does not, because the lower aggregate capital stock implies lower aggregate productivity and thus a lower capital investment return for the individual firm. Moreover, the loss in aggregate productivity in the second case makes the short-run effect of the monetary policy shock on stock prices much stronger (in the simplified model it is about 10 times stronger) than under exogenous growth. So any short- or long-run restriction imposed on the reaction of stock prices to monetary policy shocks essentially boils down to choosing either model world 1.) or 2.), without letting the data decide which one fits best. The recent papers of Moran and Queralto (2018) or Bianchi et al. (2019) find that a positive monetary policy shock decreases medium-run aggregate TFP, which is a clear hint for the second model world, while Bjørnland and Leitemo (2009) or Kontonikas and Zekaite (2018), by imposing a zero restriction on the long-run effect of monetary policy shocks on stock prices, seem to favor the first model world.

Furthermore, interpret a stock price shock as news about higher future productivity that, however, has no effect on current productivity like in Beaudry and Portier (2006). For instance assume that the productivity factor A is no longer a constant, but time dependent. Assume now that everyone gets the information that in the next period $A'_{t+1} > A^*_{t+1}$. From equation (4.10) it becomes evident that an increase in future dividends leads to an increase in stock prices now. Because the news lets the households believe to be richer in the future, the Euler equation (4.1) also implies increasing consumption today $c'_t > c^*_t$. From equations (4.6) and (4.11) it becomes evident that the higher marginal productivity of future capital increases investment $j'_t > j^*_t$. Assume the aggregate resource constraint to be that output equals the sum of consumption and investment $y_t = c_t + j_t$, then $y'_t > y^*_t$ immediately follows. A central bank aiming to flatten business cycle fluctuations would immediately increase its policy rate. Indeed, for instance Rigobon and Sack (2003) find significant policy responses of the FED to fluctuations in the S&P500 index, where a five percent increase in the stock price index increases the likelihood of a 25 basis point increase in the FFR by about 50%. Consequently, stock prices will contemporaneously react to monetary policy shocks, as will monetary policy to stock market shocks.

Now the econometrician's task would be to let the data decide, which of the two theoretical approaches is correct. Of course, we need to make some assumptions to identify the structural shocks. However, we know that a monetary policy shock will immediately influence stock prices and vice versa, so we cannot impose a short-run restriction. Imposing a long-run restriction on the effect of the monetary policy shock on stock prices means to ex ante decide that the model with decreasing returns is the right one and not the endogenous growth model, which strips us of the ability to let the data decide. Thus one is in need of a data-driven identification approach, which is the objective of the present paper.

4.2.2 SVAR models

As a second step we review the approaches of the related literature to estimate the interaction of monetary policy and the stock market in an SVAR. We show that there is a lack of a compelling estimation approach that is feasible, not too restrictive for the problem at hand and has a sufficiently good small sample performance to draw some conclusive evidence about the short- and long-run effects of monetary policy and stock market shocks.

In an SVAR, a vector of time series is explained by its past values and a linear combination of structural shocks that forms the reduced form errors

$$y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + u_t, \quad (4.12)$$

$$u_t = B\varepsilon_t, \quad (4.13)$$

with an n-dimensional vector of macroeconomic variables y_t, parameter matrices $A_1, ..., A_p$, a non-singular matrix B, the n-dimensional vector of structural shocks ε_t and the n-dimensional vector of reduced form shocks u_t. Here, the vector of structural shocks will contain a monetary policy and a stock market shock. The goal is to identify both shocks and estimate their impact on the macroeconomic variables. The VAR imposes only little a priori structure, however, without further assumptions the structural shocks are not identified and cannot be retrieved by the estimation procedure.

In general, the probably most frequently used identifying assumption for an SVAR is a recursive ordering, meaning zero restrictions on the short-run impact of some shocks, such that each variable is simultaneously only influenced by shocks ordered in rows below the variable. However, in the case of monetary policy and the stock market, zero restrictions on the interaction of both variables are hardly credible.

On the one hand, stock prices can contain news about future productivity, see Beaudry and Portier (2006). Therefore, a positive stock price shock might indicate a future boom accompanied by inflationary pressure and a stabilizing central bank would respond immediately. Consequently, a zero restriction on the response of monetary policy to stock market shocks is difficult to defend. On the other hand, stock prices are generally believed to contain all the information currently available at the stock market, which leads Beaudry and Portier (2006) to argue that news can be captured by observing stock prices. As a monetary policy shock induced by the central bank is a publicly available information, one would assume that stock prices also immediately react to exogenous changes in the interest rate. Nevertheless, zero restrictions on the interaction of monetary policy and the stock market have been used to estimate the interaction of both variables, see e.g. Laopodis (2013). However, these estimates only reflect the interaction of monetary policy and the stock market, if the identifying assumption is correct, which is at best questionable. Furthermore, one could argue that a zero restriction is only a specific short-run restriction, so knowing the correct short-run effect of a stock market shock on the nominal interest rate or of a monetary policy shock on stock prices would suffice to identify the two structural shocks. Unfortunately such knowledge does not exist and there is a broad band of possible impact effects for both shocks estimated by the related literature that does not use any short-run restrictions. Consequently, there is no conclusive evidence that justifies the use of any specific short-run restriction.

Due to the unavailability of credible short-run restrictions on the interaction of monetary policy and the stock market, several authors identify the shocks based on restrictions of the long-run interaction of both variables (see e.g. Bjørnland and Leitemo (2009) or Kontonikas and Zekaite (2018)). In particular, these authors assume long-run neutrality of monetary policy, meaning the monetary policy shock has no long-run impact on real stock prices. Bjørnland and Leitemo (2009) find that monetary policy and the stock market interact simultaneously. In particular, a tightening of monetary policy leads to an immediate decrease of stock prices and a positive stock market shock leads to an immediate tightening of monetary policy. Again, these results only reflect the true interaction of both variables, if the identifying long-run restriction is correct. In contrast to the short-run restriction used in Laopodis (2013), the long-run restriction used in Bjørnland and Leitemo (2009) is based on a widespread underlying theory that argues in favor of long-run neutrality of monetary policy. However, as shown in section 4.2.1, a slight modification of the theory from exogenous to endogenous growth already breaks the long-run neutrality result. In fact, recent studies (see e.g. Moran and Queralto

(2018), Bianchi et al. (2019) and Jordà et al. (2020)) consistently find that monetary policy affects real variables much longer than usually assumed[3]. These results cast doubt on the validity of the long-run restriction on the effect of monetary policy shocks on stock prices employed by Bjørnland and Leitemo (2009) or Kontonikas and Zekaite (2018) and the corresponding estimated interaction of monetary policy and the stock market.

Alternatively, Rigobon and Sack (2004) propose an estimator, which does not require any restrictions on the short- or long-run interaction of the stock market and monetary policy. Instead, it is based on the assumption of heteroskedastic shocks and requires to a priori specify periods of different variances of the monetary policy shocks. The identification is thus based on a stochastic property of the structural shocks and not on a restriction on the impact of the shocks. Specifying volatility regimes of monetary policy may be straight-forward on a daily basis (by choosing all days with FOMC announcements), however, with lower frequency data it becomes increasingly difficult or even impossible if the regime changes cancel out each other during longer observation periods. Therefore, the estimator becomes infeasible in typical macroeconomic applications with monthly, quarterly or even lower frequency data and excludes potential control variables that are not observed at a high frequency.

In general, identification based on time-varying volatility does not require to a priori specify volatility periods (see e.g. Rigobon and Sack (2003), Lanne et al. (2010), Lütkepohl and Netšunajev (2017) or Lewis (2019)). In fact, a latent volatility process can be used for identification without imposing much structure on the latent process. However, Lütkepohl and Netšunajev (2017) argue that reliable estimators based on GARCH or Markov switching processes are only available in small models with only a few volatility states. The intuition is simple: The more (correct) structure is imposed on the latent process, the more precise the corresponding estimate. Therefore, Lütkepohl and Netšunajev (2017) propose an estimator which imposes a parametric smooth transition function between two states of the variance-covariance matrix of the reduced form shocks. The estimator is applied to analyze the interaction of monetary policy and the stock market. The authors find a small simultaneous negative response of the stock market to a tightening of monetary

[3]Moran and Queralto (2018) and Bianchi et al. (2019) find that the impulse response of TFP is significantly positive even 15 years after a negative monetary policy shock has hit the economy. Again as in the previous section, higher productivity goes hand in hand with higher expected dividends. Therefore, stock prices should not only decrease immediately, but permanently in response to an unexpected tightening of monetary policy, as long-run productivity and thus long-run dividends decline.

policy. However, a tightening of monetary policy is also found to lead to an initial increase of inflation and output. Due to the counterintuitive response of output and inflation to the shock, the authors admit that labeling the shock as a monetary policy shock in a "conventional" sense may be misleading. Additionally, the authors are not able to label a stock market shock and hence it remains unclear, how monetary policy reacts to a stock market shock.

Another branch of the SVAR literature uses non-Gaussian and independent shocks for identification (see e.g. Lanne et al. (2017), Gouriéroux et al. (2017), Guay (2021), Lanne and Luoto (2021) and Keweloh (2019)). Theses approaches are also data-driven and do not require to impose any short- or long-run restrictions. Instead, these approaches require that the structural shocks are mutually independent and at most one shock is allowed to be Gaussian. Intuitively, non-Gaussian shocks do contain information in moments beyond the variance, which allow to identify the simultaneous interaction. In a short application, Lanne et al. (2017) use a data-driven identification approach imposing non-Gaussian and independent shocks to estimate the interdependence of monetary policy and the stock market. The authors find that an unexpected tightening of monetary policy has an immediate negative impact on financial conditions. However, they are unable to label a stock market shock. Therefore, it again remains unclear how stock market shocks influence monetary policy. We show later on that a major problem with this approach is that it becomes increasingly less useful in larger applications, as the precision of the estimates declines tremendously in that case. A completely unrestricted identification approach is thus possible, but may result in a loss of insight about the effect the structural shocks have on the observed variables the more control variables are included in the SVAR. In this paper we want to include a set of further controls like output, investment and inflation to have a closer look on the implications of monetary policy and stock market shocks and we show that in this case an approach completely relying on higher moments yields broad confidence bands, which do not allow to draw insightful conclusions about the shock effects.

To sum up, the commonly used short- and long-run restrictions regarding the interaction of monetary policy and the stock market have implications on the underlying data generating process. Until now, there is no consensus about which theoretical model is correct and the estimation should not depend on an a priori restriction favoring one or another model, but rather the data should be able to decide, which model fits the data best. On the other side, there are identification approaches that do not rely on short- or long-run restrictions, but they are either not able to be generalized to a broader macroeconomic setup or become less feasible the more variables are included into the VAR. Ideally, the SVAR estimator should allow to factor in a priori restrictions that one is certain about, but also allow a data-driven identification, if one is not certain about the underlying theory. In the following section we propose an estimator that fulfills these criteria.

4.3 A partly recursive, partly non-Gaussian SVAR estimator

A non-Gaussian SVAR with independent shocks can be estimated based on restrictions governing the interaction of the variables or based on information contained in moments beyond the variance and without any assumptions on the interaction of the variables. At first glance, in a non-Gaussian SVAR and from an asymptotic point of view, the traditional identification approach based on restrictions appears to be unnecessarily restrictive. However, we show that in a small sample the performance of a data-driven estimator based on non-Gaussianity quickly deteriorates with an increasing model size, while the performance of a restriction based estimator is less affected by the model and sample size. Moreover, the poor small sample performance then might lead to highly imprecise estimates of the structural impulse responses that make it difficult to label the resulting structural shocks, as the SVAR estimator based on the non-Gaussianity of the structural shocks is only identified up to labeling. Another caveat against the data-driven identification approach is that there might be more than one Gaussian structural shock, which makes the solely data-driven approach invalid. However, in macroeconomic applications, one can oftentimes derive at least some credible short-run zero restrictions based on economic theory, one just cannot derive sufficiently many restrictions to fully identify the SVAR based on second moments and the researcher is forced to rely on additional, less credible restrictions or to use an unreliable data-driven estimator.

The estimator proposed in this section combines the traditional restriction based approach with the more recently developed data-driven approach based on non-Gaussianity. Our estimator allows the researcher to rely on recursiveness restrictions if possible and to be agnostic on the interaction of the variables and relying on data-driven identification when necessary. In particular, the proposed estimator allows to order some, but not all, shocks recursively. While the impact of the recursive shocks is estimated based on second moments, the impact of the non-recursive shocks is estimated based on non-Gaussianity. We show that in comparison to an unrestricted estimator solely based on non-Gaussian and independent shocks, exploiting the partly-recursive structure

i) improves the finite sample performance of the estimator,

ii) reduces the burden of labeling the shocks and

iii) relaxes the non-Gaussianity and independence assumptions, where they are not applicable.

For that matter we believe the proposed estimator is dominant to a solely data-driven or solely restriction based approach and is a useful addition to the econometrician's toolbox. Additionally it allows us to get a deeper insight regarding the effect of monetary policy and stock market shocks on the nominal interest rate and stock prices.

4.3.1 Derivation of the estimator

Consider a partly-recursive SVAR, meaning there exists a subset of $m \in \mathbb{N}$ variables within a full set of observables n in an SVAR, so $0 \leq m \leq n$, for which the matrix B that translates structural shocks into the reduced form errors according to equation (4.13) reads

$$B = \begin{bmatrix} b_{11} & 0 & & \dots & & 0 \\ \vdots & \ddots & \ddots & & & \vdots \\ b_{m1} & \dots & b_{mm} & 0 & \dots & 0 \\ b_{m+1,1} & \ddots & b_{m+1,m} & b_{m+1,m+1} & & b_{m+1,n} \\ \vdots & & & \vdots & & \vdots \\ b_{n1} & \dots & b_{nm} & b_{n,m+1} & & b_{nn} \end{bmatrix}. \tag{4.14}$$

Therefore, the first m variables are ordered recursively, meaning they cannot contemporaneously be influenced by structural shocks in rows ordered below. However, the last $n - m$ variables are not ordered recursively and can contemporaneously be influenced by all structural shocks. Since the matrix B is only partly-recursive, it cannot be identified solely by second moments. However, the partly-recursive structure can be combined with estimators based on independent and non-Gaussian shocks.

The partly-recursive SVAR can be estimated in three steps. For simplicity, consider an SVAR with four variables and the following partly-recursive structure

$$\begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \end{bmatrix}. \tag{4.15}$$

The recursive part can be written as

$$\begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} b_{11} & 0 \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix}, \tag{4.16}$$

which is a simple recursive SVAR and can be identified and estimated based on second moments (e.g. by applying the Cholesky decomposition to the variance-covariance matrix of the reduced form shocks, see Kilian and Lütkepohl (2017)). The non-recursive part can be written as

$$\begin{bmatrix} u_3 \\ u_4 \end{bmatrix} = \begin{bmatrix} b_{31} & b_{32} \\ b_{41} & b_{42} \end{bmatrix} \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} + \begin{bmatrix} \nu_3 \\ \nu_4 \end{bmatrix}, \tag{4.17}$$

with

$$\begin{bmatrix} \nu_3 \\ \nu_4 \end{bmatrix} = \begin{bmatrix} b_{33} & b_{34} \\ b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \varepsilon_3 \\ \varepsilon_4 \end{bmatrix}. \tag{4.18}$$

Using the estimated structural shocks $\hat{\varepsilon}_1$ and $\hat{\varepsilon}_2$ from the first step allows to estimate the lower-left block of B in equation (4.17) by OLS. The residuals ν in equation (4.17) represent the variation in u_3 and u_4, which is unexplained by the structural shocks in the recursive block and can be explained by the shocks in the non-recursive block with equation (4.18), which yields a non-recursive SVAR. The structural shocks of the non-recursive block are globally identified up to labeling if the shocks of the block are mutually independent and at most one shock is Gaussian. The non-recursive lower-right block of B can then be estimated by an estimator based on higher moments of non-Gaussian and independent shocks, see e.g. Lanne et al. (2017), Gouriéroux et al. (2017), Lanne and Luoto (2021) or Keweloh (2019).

If the SVAR is only block recursive, such that there exists a subset of $m \in \mathbb{N}$ variables within a full set of observables n in an SVAR, so $0 \leq m \leq n$, for which the matrix B that translates structural shocks into the reduced form errors according to equation (4.13) reads

$$B = \begin{bmatrix} b_{11} & ... & b_{m1} & 0 & \dots & 0 \\ \vdots & \ddots & \ddots & \vdots & & \vdots \\ b_{m1} & \dots & b_{mm} & 0 & \dots & 0 \\ b_{m+1,1} & \ddots & b_{m+1,m} & b_{m+1,m+1} & & b_{m+1,n} \\ \vdots & & & \vdots & & \vdots \\ b_{n1} & \dots & b_{nm} & b_{n,m+1} & & b_{nn} \end{bmatrix}, \tag{4.19}$$

the approach proposed above yields inconsistent estimates for the upper-left and lower-left block of B, but remains consistent for the lower-right block[4].

The partly recursive, partly non-Gaussian estimator can also be calculated in a single step. For example, a partly-recursive version of the GMM estimator proposed in Keweloh (2019) can be obtained by including the second-order moment conditions of all shocks and the higher-order moment conditions associated with the shocks in the non-recursive block. Some estimators based on non-Gaussianity rely on an initial whitening step, see e.g. the PML estimator proposed in Gouriéroux et al. (2017) or the whitened GMM estimators proposed in Keweloh (2019). In the preliminary whitening step, the reduced form shocks are transformed into uncorrelated shocks with unit variance and in the second step, the optimization is performed over orthogonal matrices, which correspond to rotations of the transformed reduced form shocks[5]. Whitening is equivalent to an optimization subject to the constraint that the estimated structural shocks are uncorrelated with unit variance in the given sample, compare Keweloh (2019). However, in the partly-recursive SVAR defined in equation (4.14), the first m columns of B are uniquely determined by the whitening constraint, imposing that the estimated structural shocks have to

[4] Falsely imposing a recursive order in equation (4.16) yields inconsistent estimates of the upper-left block of B. Additionally, using the shocks of the first step, here $\hat{\varepsilon}_1$ and $\hat{\varepsilon}_2$, to estimate equation (4.17) will also yield inconsistent estimates of the lower-left block of B. However, if the shocks in the non-recursive block, here ε_3 and ε_4, have no simultaneous impact on the variables in the first block, the shocks $\hat{\varepsilon}_1$ and $\hat{\varepsilon}_2$ obtained from the first step are equal to a linear combination of the true shocks ε_1 and ε_2. Therefore, the residuals ν in equation (4.17) still represent the variation in u_3 and u_4 which is unexplained by the structural shocks in the recursive block and hence, the non-recursive SVAR in equation (4.18) remains valid. The proposed estimator thus allows to identify and consistently estimate the impact of a non-recursive block of variables, as long as equation (4.19) holds, meaning that all the shocks in the second and non-recursive block have no simultaneous impact on the variables in the first block of variables.

[5] Optimizing over orthogonal matrices is computationally simple, since it can be pulled back to an optimization problem over the euclidean space, see Lezcano-Casado and Martínez-Rubio (2019). In Appendix 4.6 we propose a similar transformation for the optimization problem over orthogonal matrices with partly-recursive constraints.

be uncorrelated with unit variance. Therefore, a whitened estimator with partly-recursive constraints by definition only relies on second moments to identify and estimate the impact of the shocks in the recursive block, see Appendix 4.6 for more details.

Exploiting the partly-recursive structure yields several advantages compared to an unrestricted estimator solely identified by independence and non-Gaussianity. First, the Monte Carlo study in section 4.3.2 shows that exploiting the partly-recursive order and thus decreasing the dependence of the estimator on higher moments leads to an increase of the small sample performance of the estimator. Second, every identification approach requires to impose an a priori structure. In particular, if no restrictions on the interaction of the variables are imposed, the researcher has to impose that all shocks are independent and at most one shock is allowed to be Gaussian. Sometimes there is clear evidence in favor of non-Gaussianity, as for example in the case of financial shocks, but sometimes there is not. For instance it is unclear if inflation shocks are Gaussian or not. By moving the inflation shock into the recursive block, we do not need to impose any non-Gaussianity assumptions on the inflation shock and instead can rely on the standard argument of rigid prices. Third, a data-driven identification scheme based only on non-Gaussian and independent shocks only identifies the shocks up to labeling. Therefore, the researcher has to decide, which impulse response belongs to which shock. The task of labeling the shocks becomes increasingly difficult the more shocks are identified by this procedure, especially if the impulse responses of the variables are quite similar with respect to two or more shocks. Imposing a partly-recursive structure alleviates this burden on the econometrician, since the shocks in the recursive block are already labeled by the identifying assumptions of the partly-recursive order.

In summary, we propose an estimator for partly recursive, partly non-Gaussian SVAR models. Exploiting the partly-recursive structure allows to relax the independence and non-Gaussianity assumptions, it decreases the dependence on higher moments and it simplifies the task of labeling the estimated shocks. Consequently, our estimator poses as a compromise between a data-driven and restriction-based estimator, taking the best from both worlds. It allows to be agnostic about the interaction between variables, when there is no clear insight about the underlying mechanisms, but also does not discard useful information, when they are available. Furthermore, it also reduces the burden on the labeling task and allows for the inclusion of a broader set of control variables than standard data-driven approaches.

4.3.2 Finite sample performance

In the following Monte Carlo study, we show that data-driven estimators based on non-Gaussianity suffer from a curse of dimensionality, i.e. the bias and variance increase quickly with an increasing model size and a decreasing sample size. However, we show that exploiting the partly-recursive structure can stop the curse of dimensionality.

We simulate a partly-recursive SVAR with $n = 2$ and $n = 4$ variables. The structural shocks are drawn from a t-distribution with seven degrees of freedom[6] and the mixing matrices B are given by

$$B = \begin{bmatrix} 1 & 0 \\ 0.5 & 1 \end{bmatrix} \quad \text{and} \quad B = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0.5 & 1 & 0 & 0 \\ 0.5 & 0.5 & 1 & 0 \\ 0.5 & 0.5 & 0.5 & 1 \end{bmatrix}. \tag{4.20}$$

The Monte Carlo study analyzes the impact of imposing a partly-recursive order on the PML estimator proposed by Gouriéroux et al. (2017), where the shocks have been correctly specified as t-distributed shocks with seven degrees of freedom. In the small SVAR with $n = 2$ we impose no recursive order. In the large SVAR with $n = 4$ one estimator is calculated without imposing a recursive order and a second estimator is estimated, which uses the restriction that the first two shocks are ordered recursively.

Table 4.1 shows the mean and standard deviation of each estimated element of B depending on the model size n, the number of observations T and the choice of the estimator. The simulation shows how the performance of estimates based entirely on non-Gaussianity decreases with an increasing model size, as in the second column the standard deviations of the estimated elements of the B matrix are comparably high. Moreover, we find that this curse of dimensionality is more pronounced in smaller samples, as the standard deviations of the estimates declines with an increasing number of observations. For instance comparing the standard deviation for the 4 variable case in the second column with 150 and 5000 observations, one can see that the estimated standard deviations get approximately halved. Therefore, the simulation illustrates how in a typical macroeconomic application, which rarely contains more than a few hundred observations, data-driven estimates

[6] The shocks have been normalized to unit variance by multiplying each shock with $1/\sqrt{(v/(v-2))}$ and $v = 7$.

Table 4.1: Finite sample performance of the SVAR estimator depending on model size and number of observations

	$n = 2$ PML	$n = 4$ PML	$n = 4$ partly-recursive PML
$T = 150$	$\begin{bmatrix} \underset{(1.37)}{0.97} & \underset{(6.7)}{0.0} \\ \underset{(7.26)}{0.48} & \underset{(3.0)}{0.97} \end{bmatrix}$	$\begin{bmatrix} \underset{(2.08)}{0.92} & \underset{(6.81)}{0.01} & \underset{(6.79)}{0.01} & \underset{(7.29)}{-0.0} \\ \underset{(7.55)}{0.46} & \underset{(3.76)}{0.92} & \underset{(8.09)}{0.01} & \underset{(8.95)}{-0.0} \\ \underset{(9.12)}{0.46} & \underset{(9.66)}{0.47} & \underset{(5.48)}{0.92} & \underset{(10.1)}{-0.0} \\ \underset{(11.17)}{0.46} & \underset{(12.02)}{0.47} & \underset{(12.1)}{0.46} & \underset{(8.57)}{0.9} \end{bmatrix}$	$\begin{bmatrix} \underset{(0.94)}{1.0} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(1.28)}{0.5} & \underset{(0.95)}{0.99} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(1.56)}{0.5} & \underset{(1.23)}{0.5} & \underset{(1.35)}{0.96} & \underset{(6.96)}{-0.01} \\ \underset{(1.78)}{0.5} & \underset{(1.48)}{0.5} & \underset{(7.36)}{0.49} & \underset{(3.15)}{0.96} \end{bmatrix}$
$T = 500$	$\begin{bmatrix} \underset{(1.1)}{0.99} & \underset{(5.87)}{0.0} \\ \underset{(6.22)}{0.5} & \underset{(2.46)}{0.99} \end{bmatrix}$	$\begin{bmatrix} \underset{(1.47)}{0.98} & \underset{(6.32)}{0.0} & \underset{(6.4)}{-0.0} & \underset{(6.32)}{0.0} \\ \underset{(6.65)}{0.49} & \underset{(3.12)}{0.98} & \underset{(7.83)}{-0.0} & \underset{(8.01)}{0.0} \\ \underset{(8.32)}{0.49} & \underset{(8.12)}{0.49} & \underset{(4.56)}{0.98} & \underset{(8.91)}{-0.0} \\ \underset{(9.58)}{0.49} & \underset{(10.16)}{0.49} & \underset{(9.43)}{0.49} & \underset{(6.21)}{0.98} \end{bmatrix}$	$\begin{bmatrix} \underset{(0.97)}{1.0} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(1.23)}{0.5} & \underset{(1.01)}{1.0} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(1.46)}{0.5} & \underset{(1.27)}{0.5} & \underset{(1.12)}{0.99} & \underset{(5.68)}{-0.0} \\ \underset{(1.72)}{0.5} & \underset{(1.47)}{0.5} & \underset{(5.93)}{0.5} & \underset{(2.61)}{0.99} \end{bmatrix}$
$T = 5000$	$\begin{bmatrix} \underset{(1.0)}{1.0} & \underset{(4.57)}{0.0} \\ \underset{(4.8)}{0.5} & \underset{(2.17)}{1.0} \end{bmatrix}$	$\begin{bmatrix} \underset{(0.98)}{1.0} & \underset{(4.68)}{0.0} & \underset{(4.55)}{0.0} & \underset{(4.41)}{0.0} \\ \underset{(4.98)}{0.5} & \underset{(2.18)}{1.0} & \underset{(5.67)}{0.0} & \underset{(5.65)}{0.0} \\ \underset{(5.88)}{0.5} & \underset{(5.95)}{0.5} & \underset{(3.34)}{1.0} & \underset{(6.79)}{0.0} \\ \underset{(6.89)}{0.5} & \underset{(6.9)}{0.5} & \underset{(6.95)}{0.5} & \underset{(4.53)}{1.0} \end{bmatrix}$	$\begin{bmatrix} \underset{(0.96)}{1.0} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(1.24)}{0.5} & \underset{(0.98)}{1.0} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(1.49)}{0.5} & \underset{(1.21)}{0.5} & \underset{(1.01)}{1.0} & \underset{(4.47)}{0.0} \\ \underset{(1.68)}{0.5} & \underset{(1.5)}{0.5} & \underset{(4.66)}{0.5} & \underset{(2.17)}{1.0} \end{bmatrix}$

Monte Carlo simulation with sample sizes 150, 500, and 5000 each with 5000 iterations. The simulated SVAR has $n = 2$ or $n = 4$ variables and the diagonal of the mixing matrix B is equal to 1, the lower-left triangular of B is equal to 0.5 and the upper-right triangular of B is equal to 0. The structural shocks are drawn from a t-distribution with $v = 7$ degrees of freedom and have been normalized to unit variance shocks by multiplying each shock with $1/\sqrt{(v/(v-2))}$. The SVAR is estimated by the PML estimator proposed by Gouriéroux et al. (2017), where the shocks have been correctly specified as t-distributed shocks with seven degrees of freedom. The last column shows the PML estimator with the restriction that the first two shocks are ordered recursively. The table shows the mean of $\hat{b}_{ij}$ and in parentheses the standard deviation of $\sqrt{T}(\hat{b}_{ij} - b_{ij})$ of all estimated elements $\hat{b}_{ij}$.

based on non-Gaussianity become less reliable the more variables and thus shocks the SVAR contains. However, the simulation also shows that exploiting the (correct) partly-recursive structure stops the deterioration of the performance induced by a larger model and a smaller sample. We conclude that discarding any available information comes with the cost of worse small sample performance, which reduces the usefulness and conclusiveness of the estimation. In the larger SVAR with $n = 4$ variables, the first two columns of the partly-recursive PML estimator for the matrix B are fixed by the whitening step as explained before and are thus entirely determined by second moments[7] and only the unrestricted elements of the last two columns depend on higher moments. However, these unrestricted elements perform very similar to the estimates of the small model with $n = 2$. Therefore, the simulation shows that including a priori information on the recursive order can break the curse of dimensionality of the data-driven estimator based on non-Gaussianity. For example comparing the standard deviations for the 4 variable case and 150 observations concerning the fully data-driven and partly-recursive SVAR estimator (first row, second and third column of table 4.1) shows that exploiting the partly-recursive structure leads to an increase in accuracy by a factor up to 12 for the freely estimated elements of the matrix B in our simulation.

In macroeconomic applications, one oftentimes faces relatively large models but only small samples with at best a few hundred observations. In this case, purely data-driven estimates based on non-Gaussianity become volatile and in a given application it can become difficult to draw any conclusions on the interaction of the variables or to even label the shocks. However, econometricians have put much work into deriving and defending restrictions on the interaction of macroeconomic variables and the simulation shows, how including traditional zero restrictions increases the finite sample performance of a data-driven estimator based on non-Gaussianity. Therefore, we argue that in a given application, the researcher should include restrictions when possible and rely on a data-driven estimation when necessary.

4.4 The interdependence of monetary policy and stock markets in U.S. data

In this section, we apply the proposed estimator to analyze the effect of monetary policy and stock market shocks on a set of macroeconomic variables. Our SVAR contains a first block of recursively ordered variables, in particular output growth, investment growth and inflation, and a second block consisting of stock returns and the Federal Funds Rate, where we do not restrict the short- or long-run effect of the structural monetary policy and stock market shock in any way. We first apply our partly-recursive SVAR estimator and impose that the first block is ordered recursively, however, the second block containing the monetary policy and

[7] The first two columns of the unrestricted PML estimator depend on higher moments. Comparing the first two columns of the unrestricted and partly-recursive estimator shows the possible performance gains of decreasing the dependence of the estimator on higher moments. However, note that this difference is driven by the degree of non-Gaussianity of the shocks and more or less Gaussian shocks would result in a smaller or larger difference.

stock market shock remains unrestricted. Afterwards, we apply an unrestricted, purely data-driven estimator, to check on the validity of our recursive ordering for the first block of variables. Both estimators indicate that a tightening of monetary policy leads to an immediate and likely permanent decrease in stock prices, while a positive stock market shock leads to an immediate increase in interest rates. Additionally, the unrestricted estimation indicates that the macroeconomic variables do not simultaneously respond to stock market and monetary policy shocks and hence it supports the partly-recursive order. However, the unrestricted and purely data-driven estimation leads to large confidence intervals and the dynamics, which potentially explain the interaction of monetary policy and the stock market, remain hidden. In contrast to that, the partly-recursive estimator yields smaller confidence bands and we find that a tightening of monetary policy is followed by a recession, which explains the decrease in stock returns, while a stock market shock behaves equivalent to a news shock and indicates a business cycle expansion with an increase in output and inflation, which explains the response of monetary policy.

We consider an SVAR in five variables and quarterly U.S. data from 1983Q1 to 2019Q1 of the form

$$\begin{bmatrix} y_t \\ I_t \\ \pi_t \\ i_t \\ s_t \end{bmatrix} = \alpha + \gamma t + \sum_{i=1}^{p} A_i \begin{bmatrix} y_{t-i} \\ I_{t-i} \\ \pi_{t-i} \\ i_{t-i} \\ s_{t-i} \end{bmatrix} + \begin{bmatrix} u_t^y \\ u_t^I \\ u_t^\pi \\ u_t^i \\ u_t^s \end{bmatrix}, \tag{4.21}$$

where y denotes output growth, I investment growth, π the inflation rate, i the federal funds rate and s real stock returns[8]. Moreover, we set $p = 2$ as suggested by the Akaike information criterion. The linear time trend t is added to catch an eventual long-term decline in the interest rate as discussed by Carvalho et al. (2016). We choose a specification in growth rates to remain close to Bjørnland and Leitemo (2009) or Kontonikas and Zekaite (2018) in order to have a better comparability between their results and ours and to check on the validity of a potential long-run

[8]The inflation rate is defined as the quarter to quarter growth rate in the quarterly chain-type GDP price index retrieved from the FRED. The GDP growth rate is given by the quarterly log-difference of real GDP retrieved from the FRED. Real investment growth is given by the quarterly growth rate of real gross private domestic investment obtained from the FRED. The nominal interest rate is defined as the Federal Funds Rate (FFR), where the effective FFR (retrieved from FRED) is replaced by the shadow FFR provided by Wu and Xia (2016) for the Zero Lower Bound observations during the Great Recession. Stock returns are defined as the quarterly log-difference in real stock prices, where real stock prices are given by the S&P 500 index (retrieved from macrotrends.net) divided by the chain-type GDP price index.

constraint on the effect of monetary policy shocks on stock prices, as the validity of a long-run restriction requires the cumulative growth effect to equal zero.

Appendix 4.7 contains multiple robustness checks covering the exclusion of the time trend, inclusion of further variables, exclusion of the financial crisis starting in 2008, different lag structures, estimating a specification using an industrial production index for output as in Bjørnland and Leitemo (2009) or using a different non-Gaussian estimator. Our main results remain unchanged: Stock prices and the nominal interest rate both react immediately to monetary policy and stock market shocks, indicating that these variables cannot be ordered recursively. However, across specifications we cannot fully reject the long-run neutrality assumption, but also do not find much evidence for its validity. In consequence, we deem our new estimator as a more reliable tool to analyze the interrelationship between stock markets and monetary policy.

4.4.1 Partly-recursive estimation

We first assume that real investment growth, real output growth and inflation are ordered recursively in a first block of variables and behave sluggishly, meaning they cannot react to shocks to variables ordered below and especially not to monetary policy or stock market shocks within the same quarter. For instance the seminal paper of Stock and Watson (2001) assumes that inflation is contemporaneously unaffected by surprise changes in the nominal interest rate based on a Granger causality analysis. With a rigid labor market as discussed in Mortensen and Pissarides (1994), employment is unaffected by monetary policy and capital as well as productivity are predetermined stock variables, so in consequence also output should not be affected contemporaneously. Furthermore, economic theory has come up with ideas like habit formation in consumption, varying capital utilization and investment adjustment costs that induce sluggish responses of consumption and investment. Regarding shocks to the stock market, Beaudry and Portier (2006) assume investment and output to respond only with a one quarter lag, as news shocks show up immediately in stock prices, but need time to manifest in other economic variables. Given this empirical evidence and theoretic deliberations, we feel confident to in a first step put output growth, investment growth and inflation into the recursive block. But, again, we check on the validity of these assumptions afterwards. Interest rates and stock returns are, however, unrestricted and can contemporaneously respond to all shocks. Therefore, the simultaneous relationship between reduced form errors and structural shocks is given by

$$\begin{bmatrix} u_t^y \\ u_t^I \\ u_t^\pi \\ u_t^i \\ u_t^s \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 & 0 \\ b_{31} & b_{32} & b_{33} & 0 & 0 \\ b_{41} & b_{42} & b_{43} & b_{44} & b_{45} \\ b_{51} & b_{52} & b_{53} & b_{54} & b_{55} \end{bmatrix} \begin{bmatrix} \varepsilon_t^y \\ \varepsilon_t^I \\ \varepsilon_t^\pi \\ \varepsilon_t^s \\ \varepsilon_t^i \end{bmatrix}. \tag{4.22}$$

Again, note that the zero restrictions on the elements b_{12}, b_{13} and b_{23} are not necessary for the identification of the non-recursive block. We still impose them here, as in the appendix we check on the properties of the remaining shock impulse responses and we find that also the recursively identified output, investment and inflation shocks have the expected impact on the observed variables, for a further discussion see the appendix. The estimator proposed in section 4.3 allows to identify the impact of the monetary policy shock ε_t^i and the stock market shock ε_t^s without committing to any further restrictions, if the monetary policy and stock market shocks are independent and at least one of the two shocks is non-Gaussian. Non-Gaussianity is a commonly found feature of financial variables, see e.g. Mittnik et al. (2000) or Kim and White (2004), so there is evidence that stock market shocks are likely to be non-Gaussian, which would be sufficient for our identification approach here. Table 4.2 shows the skewness, kurtosis and the Jarque-Bera test (H0: shocks are normally distributed) for normality of the reduced form shocks. As becomes evident, we find 3 of the 5 reduced form errors to be non-Gaussian at

Table 4.2: Non-Gaussianity reduced form

	u^y	u^I	u^π	u^i	u^s
Skewness	−0.73	0.10	−0.03	−0.58	−1.13
Kurtosis	5.13	3.75	2.84	4.33	11.09
JB-Test	0.00	0.16	0.92	0.00	0.00

Skewness, kurtosis and the p-value of the Jarque-Bera test for normality (H0: shock is normally distributed) of the reduced form shocks.

standard significance levels, which indicates that there has to be at least some non-Gaussianity in the structural shocks, as a combination of only Gaussian structural shocks would result in Gaussian reduced form errors. In many applications, the researcher is only interested in some structural shocks. In this case, our proposed partly-recursive identification approach is robust to various misspecifications, in fact one only needs a block-recursive structure, where the variables in a first block are not influenced by shocks in a second block. For simplicity, consider the following

SVAR with two blocks

$$\begin{bmatrix} u_{p_1} \\ u_{p_2} \end{bmatrix} = \begin{bmatrix} B_{11} & 0 \\ B_{21} & B_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{p_1} \\ \varepsilon_{p_2} \end{bmatrix}, \quad \tilde{\varepsilon}(X) = X^{-1}u, \quad \text{and} \quad X = \begin{bmatrix} X_{11} & 0 \\ X_{21} & X_{22} \end{bmatrix}, \tag{4.23}$$

where u_{p_1} and u_{p_2} contain the reduced form shocks of the first and second block, ε_{p_1} and ε_{p_2} contain the structural shocks of the first and second block, and B_{11}, B_{21}, B_{22}, X_{11}, X_{21}, and X_{22} are the corresponding blocks of the matrices B and X. For any invertible X satisfying the block-recursive structure and the covariance conditions $0 = E\left[\tilde{\varepsilon}_{p_2}(X)\tilde{\varepsilon}_{p_1}(X)'\right]$, which ensure that the unmixed innovations of block one and two are uncorrelated, it holds that the unmixed innovations of the second block satisfy

$$\tilde{\varepsilon}_{p_2}(X) = X_{22}^{-1} B_{22} \varepsilon_{p_2}, \tag{4.24}$$

meaning they are only a mixture of structural shocks from the second block.[9] Therefore, if the covariance conditions $0 = E\left[\tilde{\varepsilon}_{p_2}(X)\tilde{\varepsilon}_{p_1}(X)'\right]$ are satisfied, the moment conditions containing only unmixed innovations of the second block identify the shocks in the second block and their impact $X_{22} = B_{22}$. Consequently, identification of the shocks in a given block does not depend on whether the shocks in the previous block are identified, as long as the shocks are uncorrelated with the shocks in the previous block. Table 4.3 shows the skewness, kurtosis and the Jarque-Bera test for normality of the estimated structural shocks ε^s and ε^i: We find strong

Table 4.3: Non-Gaussianity of estimated structural shocks

	ε^s	ε^i
Skewness	−0.547	−0.612
Kurtosis	4.023	14.692
JB-Test	0.001	0.00

Skewness, kurtosis and the p-value of the Jarque-Bera test for normality of the estimated structural shocks.

evidence that both of the estimated structural shocks in the second block are non-Gaussian, which is sufficient for an identification of the second block shocks solely based on moments beyond the variance. We conclude that our estimator is able to consistently estimate at least the structural monetary policy and stock market

[9]To verify this, note that with the block-recursive structure and the partitioned inverse it holds that $\tilde{\varepsilon}_{p_1}(X) = X_{11}^{-1} B_{11} \varepsilon_{p_1}$ and $\tilde{\varepsilon}_{p_2}(X) = -X_{22}^{-1} X_{21} X_{11}^{-1} B_{11} \varepsilon_{p_1} + X_{22}^{-1}\left(B_{21}\varepsilon_{p_1} + B_{22}\varepsilon_{p_2}\right)$. With $E\left[\varepsilon_{p_1}\varepsilon_{p_1}'\right] = I$ and $E[\varepsilon_{p_2}\varepsilon_{p_1}'] = 0$, the condition $0 = E\left[\tilde{\varepsilon}_{p_2}(X)\tilde{\varepsilon}_{p_1}(X)'\right]$ implies $0 = -X_{22}^{-1}\left(B_{21} - X_{21}X_{11}^{-1}B_{11}\right)B_{11}'(X_{11}^{-1})'$, which only holds if $X_{21} = B_{21}B_{11}^{-1}X_{11}$. Plugging in the condition for X_{21} yields $\tilde{\varepsilon}_{p_2}(X) = X_{22}^{-1}B_{22}\varepsilon_{p_2}$.

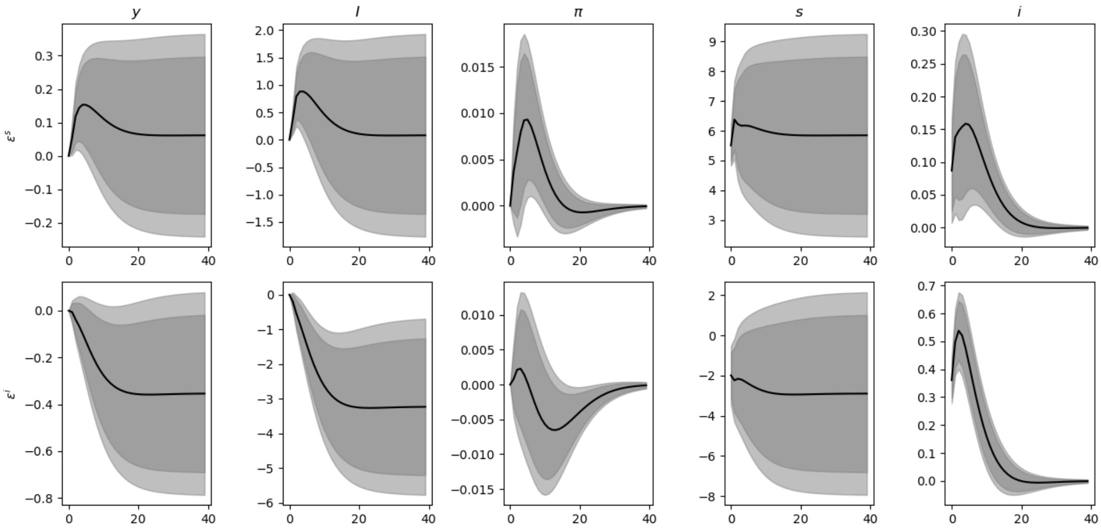
shock. Furthermore, if the assumption of a partly-recursive order in equation (4.22) is correct, the non-Gaussianity of the structural monetary policy and stock market shock does not affect the reduced form shocks in the first block, which is consistent with the result reported in table 4.2 that there is less evidenced non-Gaussianity in the first three reduced form errors. The results here cast some doubt on a fully data-driven identification approach, as we cannot exclude for sure that more than one structural shock in the first block is Gaussian. However, our partly-recursive identification scheme is able to deal with this situation, as the block with less evidenced non-Gaussianity is put into the recursive block that does not depend on the non-Gaussianity assumption.

The simultaneous interaction of the non-recursive block containing the monetary policy and stock market shock is then estimated by the fast SVAR-GMM estimator proposed in Keweloh (2019). The estimated B-matrix is given by

$$\hat{B} = \begin{pmatrix} 0.49 & 0 & 0 & 0 & 0 \\ 1.74 & 1.82 & 0 & 0 & 0 \\ 0 & 0 & 0.05 & 0 & 0 \\ 1.44 & 0.51 & -0.34 & 5.51 & -1.99 \\ 0.1 & 0.01 & 0.07 & 0.09 & 0.36 \end{pmatrix}. \tag{4.25}$$

Figure 4.2 shows the corresponding impulse response functions (IRF), where the stock market shock refers to a one standard deviation shock, which implies a 5.51% increase in stock returns and the monetary policy shock refers to a one standard deviation shock, which induces a 0.36% increase of the nominal interest rate. The responses of stock returns and real GDP growth are integrated to show the associated level effects. Exploiting the partly-recursive order makes labeling of the two structural shocks identified by the data-driven approach trivial. There is only one of the last two shocks, which leads to an increase of the interest rate together with a decrease of output and investment as well as a medium-run decrease of inflation, which is what one would expect from a classical contractionary monetary policy shock. The other shock in the non-recursive block is accordingly labeled as the stock market shock. Again the behavior of the associated impulse responses fits the theoretical expectations regarding a stock market shock: The boom at the stock market induces a positive reaction of output, investment and inflation, which fits the finding of Beaudry and Portier (2006) that a shock to the stock market induces business cycle comovement. The central bank reacts with an increase in the FFR, which fits the assumption of the central bank aiming to reduce business

Figure 4.2: Impulse responses to shocks (in this case a one standard deviation shock) in stock returns (s) and monetary policy (i). I denotes investment growth, y output growth and π the inflation rate. Confidence bands are 68% and 80% bootstrap bands. 5000 replications are used in the bootstrap algorithm. The columns y, I and s show the cumulative responses.



cycle fluctuations.

We find that both, stock returns and the nominal interest rate, react contemporaneously to the monetary policy and stock market shocks. In particular, a one standard deviation stock market shock leads to an interest rate increase of about nearly 0.15 percentage points within the first five quarters. On the other side, a one standard deviation monetary policy shock leads to an immediate decrease of stock prices by about 2% on impact. Consistent with the news literature around Beaudry and Portier (2006), we find that a positive stock market shock is followed by a future business cycle expansion with an increase in the real output and investment growth rate and a positive inflation rate. Therefore, even if the central bank is not interested in stock prices in the first place, a stock market shock can indicate a future business cycle expansion with inflationary pressure, which explains the estimated positive response of the interest rate to the stock market shock. Additionally, we find that a contractionary monetary policy shock induces a recession with a decrease in real output and investment growth, as well as a negative inflation reaction at least in the medium run. The future recession and an efficient stock market, which immediately incorporates all available information, then explains the initial negative response of stock prices to the monetary policy shock. We find that the inflation rate has a short, insignificant and small, but still unexpectedly positive reaction to a contractionary monetary policy shock on impact. This price puzzle, however, is not unique to our approach, but commonly known to the VAR literature, where it also appears in Bjørnland and Leitemo (2009) or Moran and Queralto (2018). Therefore, we do not consider the occurrence of a small insignificant price puzzle to be strong evidence against our case.

Unlike Bjørnland and Leitemo (2009) we do not impose long-run neutrality of monetary policy with respect to stock prices. Based on the point estimate we do not find long-run neutrality of monetary policy concerning stock prices, but cannot reject it considering the 80% and 68% confidence bands retrieved from bootstrap resampling. However, a long-run zero effect just lies at the edge of a broad confidence band, so there is no strong evidence for its validity either. Furthermore, we find that a contractionary monetary policy shock leads to a permanently lower real output and real investment level. Thus, according to our simple model from section 4.2, our data-driven approach would actually favor the endogenous growth and not the neoclassical model. This is in line with the recent evidence provided by Moran and Queralto (2018) or Bianchi et al. (2019), who find that monetary policy might be non-neutral in the long run. In the appendix, we show that we are not able to find any robust and clear evidence that would support long-run neutrality in any of our robustness checks.

4.4.2 Unrestricted estimation

We now check on the recursiveness assumption for the variables in the first block. Therefore, we use no restrictions on the simultaneous interaction in the first block and allow all variables to interact simultaneously. The estimation of the simultaneous interaction is purely data-driven and based on the fast SVAR-GMM estimator proposed in Keweloh (2019). We focus on the interaction of monetary policy and the stock market. The shocks have been labeled such that the monetary policy shock ε_i is the shock with the highest correlation with the reduced form shock u_i, and the stock market shock ε_s is the shock with the highest correlation with the reduced form shock u_s. The IRF shows that the shock labeled as the monetary policy shock is the only shock that leads to an increase in the interest rate accompanied by a decrease in GDP, investment and a medium-run decrease in inflation, which reinforces our labeling. We determine the labeling of a demand shock ε_d, an investment specific shock ε_I and an inflation shock ε_π also based on the highest correlation between reduced form errors and structural shocks (the correlation matrix between reduced form errors and structural shocks can be found in the appendix).

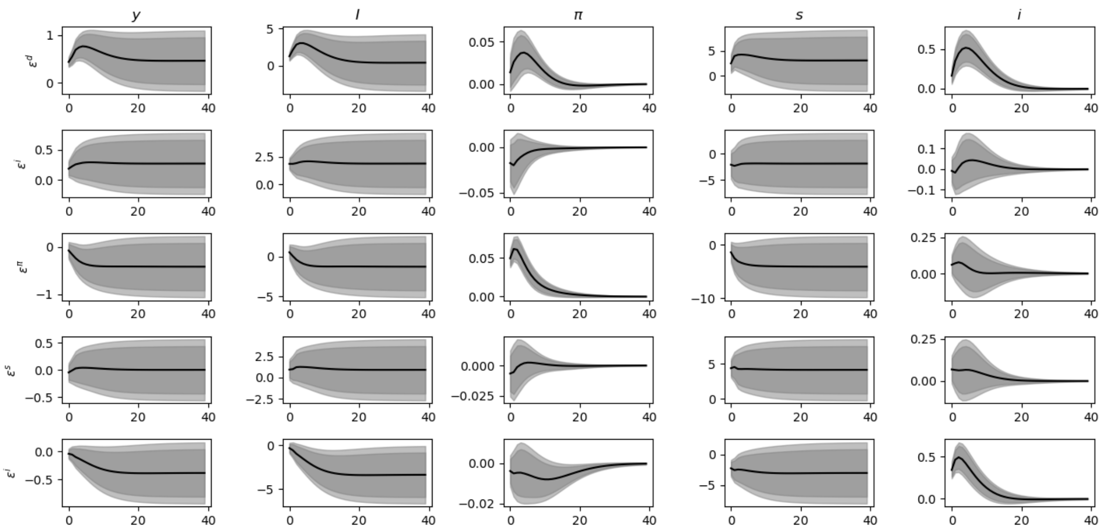
However, this labeling is to be taken with a grain of salt, as the conclusiveness of an approach only relying on higher moments for identification with 5 variables visibly deteriorates compared to the last section. For instance the first and fourth row of the impulse responses show similar qualitative results, which are associated with high uncertainty. So convincingly labeling a stock market shock and telling it apart from a demand shock becomes difficult here, which is the same problem other solely data-driven approaches face (see, e.g., Lanne et al. (2017)). This shows the benefits of including additional restrictions on the short-run interaction between variables from theory, if available, as it allows for more conclusive insights.

The estimated B-matrix is given by

$$\hat{B} = \begin{pmatrix} 0.44 & 0.19 & -0.08 & -0.04 & -0.05 \\ 1.3 & 1.84 & 0.53 & 0.94 & -0.32 \\ 0.01 & -0.02 & 0.05 & -0.01 & 0 \\ 2.48 & -2.12 & -1.38 & 4.38 & -2.23 \\ 0.16 & -0.01 & 0.06 & 0.07 & 0.34 \end{pmatrix}. \tag{4.26}$$

Figure 4.3 shows the IRFs (again to shocks of size one standard deviation on the main diagonal). The unrestricted estimation confirms our finding on the interaction

Figure 4.3: Impulse responses to shocks to all variables in the unrestricted case. Confidence bands are 68% and 80% bootstrap bands. 5000 replications are used in the bootstrap algorithm. The columns I, y and s show the cumulative responses.



of monetary policy and the stock market:

I) A tightening of monetary policy induces a recession with a decrease in output, investment, inflation, and stock prices and

II) a positive stock market shock is accompanied by an immediate increase in interest rates.

Turning to the validity of the recursivness assumption used in the partly-recursive estimation, we find that investment, GDP and inflation do not have a significant simultaneous response to monetary policy and stock market shocks (only the response of investment to stock market shocks is farther away from zero, but insignificant considering the 80% and 68% confidence band). As also the qualitative and quantitative findings are very similar to the partly-recursive case, we do not see any evidence against the correctness of our chosen identification approach.

Consistent with the finding in the Monte Carlo simulation in section 4.3.2, we find that the confidence intervals are larger compared to the partly-recursive estimation in section 4.4.1. In particular, a stock market shock appears to have almost no significant impact on investment, GDP or inflation, thus making it difficult to explain the response of the interest rate. The application illustrates, how a data-driven approach can be combined with traditional zero restrictions to impose more structure on the SVAR and thereby decrease the variance of the estimator and gain deeper insights into the transmission of stock market and monetary policy shocks.

4.5 Conclusion

The present paper proposes an SVAR estimator that is partly recursive and partly based on higher moments of non-Gaussian structural shocks, which generalizes between the traditional short- or long-run restriction based approaches and the more recently developed data-driven identification based on non-Gaussianity. We show that purely data-driven estimators based on non-Gaussian structural shocks suffer from a curse of dimensionality in small samples and large models. Exploiting a partly-recursive order for at least some variables, where it appears to be reasonable, can break the curse of dimensionality and improve the finite sample performance. The higher accuracy of the estimator yields narrower confidence bands that in turn allow for more conclusive insights about the effects of monetary policy and stock market shocks on stock returns and the nominal interest rate and an easier labeling of the structural shocks identified by the data-driven identification. Furthermore, as a fully data-driven identification approach becomes less and less useful the higher the number of variables included in the SVAR, exploiting at least some ex ante restrictions allows for larger VAR specifications and thus more controls that might increase the validity of the results. In summary, our proposed estimator enables the econometrician to drop ex ante restrictions on the shock effects where they are questionable, but to increase precision by using short-run zero restrictions where possible.

The estimator is then applied to analyze the impact of monetary policy shocks on stock prices and of stock market shocks on monetary policy. We find that contractionary monetary policy shocks have a contemporaneous negative impact on stock prices, while stock market shocks have an on impact positive effect on the nominal interest rate. Additionally, we find no strong evidence for the validity of the long-run neutrality of monetary policy with respect to stock prices, which is used for identification by the literature such as Bjørnland and Leitemo (2009) or Kontonikas and Zekaite (2018), and is in line with recent findings of Moran and Queralto (2018) and Bianchi et al. (2019), who find that monetary policy shocks are non-neutral in the long run. We are, furthermore, able to reliably introduce more control variables than fully data-driven approaches. We find that a monetary policy shock negatively affects output and investment in the longer run and that they comove with stock prices in the short and long run like predicted in standard theory, which further increases our distrust concerning a long-run zero restriction. In this setup, where both short- and long-run restrictions are questionable for the block of variables consisting of stock returns and the nominal interest rate, the proposed estimator allows to estimate the interaction of the stock market and monetary policy without imposing any restrictions on the interaction of both variables. Furthermore, we find that the effect of monetary policy and stock market shocks is reasonable and in line with standard theory concerning the remaining variables, namely output, investment and inflation. In a robustness check, we perform a fully data-driven identification and find no evidence for the inappropriateness of the short-run zero restrictions in the recursive block. However, the estimates are much less precise and do not allow to draw many conclusions concerning the effects of monetary policy and stock market shocks on the observed variables, our estimator of choice is thus the partly-recursive one proposed in the present paper.

In summary, we conclude that finding a compromise between a restriction-based and data-driven identification approach yields an estimator that neither relies on too questionable assumptions nor has a too poor small sample performance. Thus, we can perform a thorough analysis regarding the interdependence between stock prices and monetary policy and support more recent findings that the longer-run implications of monetary policy should not be disregarded.

4.6 Appendix: White SVAR estimators with partly-recursive constraints

Let $Q(B,u)$ be the objective function of a non-Gaussian SVAR estimator. Moreover, define the unmixed innovation $e(B) = B^{-1}u$. A whitened SVAR estimator then requires that $\frac{1}{T}\sum_{t=1}^{T} e_t(B)e_t'(B) = I$, such that in a given sample the unmixed innovations are mutually uncorrelated with unit variance.

Estimating a n dimensional SVAR with m partly-recursive constraints and T observations yields the following optimization problem

$$\hat{B} := \underset{B \in \mathbb{R}^{n\times n}}{\arg\min}\, Q(B,u) \tag{4.27}$$
$$s.t. \quad b_{i,j} = 0, \qquad \text{for } i < j \text{ and } i \leq m.$$

A whitened SVAR estimator has an additional constraint

$$\hat{B} := \underset{B \in \mathbb{R}^{n\times n}}{\arg\min}\, Q(B,u) \tag{4.28}$$
$$s.t. \quad b_{i,j} = 0, \quad \text{for } i < j \text{ and } i \leq m \tag{4.29}$$
$$\frac{1}{T}\sum_{t=1}^{T} e_t(B)e_t'(B) = I. \tag{4.30}$$

However, due to the whitening constraint (4.30) the optimization problem (4.28) is difficult to solve numerically.

First, we ignore the partly-recursive constraint (4.29) and consider a white SVAR estimator with the corresponding optimization problem

$$\hat{B} := \underset{B \in \mathbb{R}^{n\times n}}{\arg\min}\, Q(B,u) \tag{4.31}$$
$$s.t. \quad \frac{1}{T}\sum_{t=1}^{T} e_t(B)e_t'(B) = I$$

The constrained optimization problem (4.31) can be transformed into an unconstrained optimization problem over orthogonal matrices. Let $VV' = \frac{1}{T}\sum_{t=1}^{T} u_t u_t'$ be the Cholesky decomposition of the sample variance-covariance matrix of the reduced form shocks. For simplicity, we ignore the indeterminacy of sign and permutation. It holds that $\hat{B} = V\hat{O}$ with

$$\hat{O} := \arg\min_{O \in \mathbb{O}^{n\times n}} Q(VO, u), \tag{4.32}$$

where $\mathbb{O}^{n\times n}$ denotes the set of $n \times n$ dimensional orthogonal matrices. The optimization problem over orthogonal matrices in equation (4.32) has no constraints and can be pulled back to an optimization problem over the euclidean space, see Lezcano-Casado and Martínez-Rubio (2019). Therefore, let $exp(\cdot)$ denote the matrix exponential function. Let $s(\cdot)$ be the function, which maps a vector into a lower skew-symmetric matrix. It then holds that

$$\hat{O} := \arg\min_{\theta \in \mathbb{R}^{\frac{n(n-1)}{2}}} Q(V\mathcal{O}(\theta), u), \tag{4.33}$$

where $\mathcal{O}(\theta) = exp(s(\theta))$ maps the $\frac{n(n-1)}{2}$ dimensional vector θ into an orthogonal matrix.

Similar to the case without the partly-recursive constraints, the optimization problem (4.28) with the partly-recursive constraints (4.29) can be transformed into an optimization problem over orthogonal matrices such that $\hat{B} = V\hat{O}$ with

$$\hat{O} := \arg\min_{O \in \mathbb{O}^{n\times n}} Q(VO, u), \tag{4.34}$$

$$s.t. \quad (VO)_{i,j} = 0, \quad , \text{for } i < j \text{ and } i \leq m \tag{4.35}$$

Let $d = \frac{(n-m)(n-m-1)}{2}$ and define the mapping between a d dimensional vector into an orthogonal matrix, which preserves the partly-recursive constraint (4.35)

$$\mathcal{O}_m : \mathbb{R}^d \to \mathbb{O}^{n\times n}, \, \theta \longmapsto \begin{bmatrix} I_m & 0 \\ 0 & exp(s(\theta)) \end{bmatrix}, \tag{4.36}$$

where I_m denotes and m dimensional identity matrix. The optimization problem (4.34) can now be pulled back to an unconstrained optimization problem over the euclidean space

$$\hat{O} := \arg\min_{\theta \in \mathbb{R}^d} Q(V\mathcal{O}_m(\theta), u), \tag{4.37}$$

which simplifies the numerical optimization problem.

We now show that in an SVAR with a whitening constraint, the first m columns of the B matrix and therefore the first m recursively ordered shocks are determined by second moments due to the whitening constraint. Put differently, no information in moments beyond the variance can affect the estimated impact of the first m recursively ordered shocks, since it is entirely determined by the whitening constraint. For simplicity, consider the four dimensional example with $m = 2$

$$\begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \end{bmatrix}, \tag{4.38}$$

which can be written as

$$\begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} b_{11} & 0 \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} \tag{4.39}$$

$$\begin{bmatrix} u_3 \\ u_4 \end{bmatrix} = \begin{bmatrix} b_{31} & b_{32} \\ b_{41} & b_{42} \end{bmatrix} \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} + \begin{bmatrix} \nu_3 \\ \nu_4 \end{bmatrix} \tag{4.40}$$

$$\begin{bmatrix} \nu_3 \\ \nu_4 \end{bmatrix} = \begin{bmatrix} b_{33} & b_{34} \\ b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \varepsilon_3 \\ \varepsilon_4 \end{bmatrix}. \tag{4.41}$$

In a whitened SVAR, the unmixed innovations have to satisfy the condition

$$\frac{1}{T} \sum_{t=1}^{T} e_t(B) e_t'(B) = I. \tag{4.42}$$

In particular, the matrix B has to satisfy

$$\frac{1}{T} \sum_{t=1}^{T} e_{1,t}(B) e_{1,t}(B) = 1 \tag{4.43}$$

$$\frac{1}{T} \sum_{t=1}^{T} e_{2,t}(B) e_{2,t}(B) = 1 \tag{4.44}$$

$$\frac{1}{T} \sum_{t=1}^{T} e_{1,t}(B) e_{2,t}(B) = 0. \tag{4.45}$$

However, equation (4.39) is a recursive SVAR, which is uniquely determined by the variance and covariance conditions (4.43)-(4.45). Therefore, in a whitened SVAR the parameters b_{11}, b_{21}, and b_{22} and hence the first m estimated structural shocks, here $\hat{e}_1$ and $\hat{e}_2$, are uniquely determined by second moments. Note that this solution is equal to the solution obtained by applying the Cholesky decomposition to the variance covariance matrix of the reduced form shocks. Moreover, the whitening constraint implies

$$\frac{1}{T}\sum_{t=1}^{T}\hat{e}_{1,t}v_{3,t}(B) = 0 \tag{4.46}$$

$$\frac{1}{T}\sum_{t=1}^{T}\hat{e}_{2,t}v_{3,t}(B) = 0 \tag{4.47}$$

$$\frac{1}{T}\sum_{t=1}^{T}\hat{e}_{1,t}v_{4,t}(B) = 0 \tag{4.48}$$

$$\frac{1}{T}\sum_{t=1}^{T}\hat{e}_{2,t}v_{4,t}(B) = 0. \tag{4.49}$$

Replacing ε_1 and ε_2 with $\hat{e}_1$ and $\hat{e}_2$ in equation (4.40) and exploiting the four conditions (4.46)-(4.49) implies that the parameters b_{31}, b_{32}, b_{41}, and b_{42} are again uniquely determined by second moments. Therefore, the estimated impact of the first m recursively ordered shocks is uniquely determined by second-order moment conditions derived from the whitening constraint.

4.7 Appendix: Supplementary material and further robustness checks

This section contains supplementary material and robustness checks for the application presented in section 4.4. The estimated effect of the stock market and monetary policy shock is found to be robust to all applied robustness checks.

Table 4.4 shows some descriptive statistics of the variables used in the SVAR.

Table 4.4: Descriptive statistics

	Mean	Median	Mode	Std. deviation	Variance	Skewness	Kurtosis
y	0.71	0.74	−2.19	0.61	0.37	−0.83	3.46
I	1.1	0.96	−11.56	3.16	9.97	−0.28	2.3
π	2.28	2.09	0.27	0.87	0.76	0.36	−0.28
i	1.56	2.11	−26.45	6.5	42.25	−1.08	2.88
s	3.69	4.02	5.25	3.44	11.84	−0.03	−0.93

Table 4.5 shows the skewness, kurtosis and p-value of the Jarque-Bera test of all estimated structural shocks in the non-recursive SVAR in section 4.4.2. Judging

Table 4.5: Moments of estimated structural shocks (non-recursive SVAR)

	ε^y	ε^I	ε^π	ε^s	ε^i
Skewness	-1.0395	0.6256	-0.0878	-0.7813	-0.3616
Kurtosis	7.1174	4.0654	3.0879	5.2690	15.0522
JB-Test	0.00	0.01	0.891	0.00	0.00

Skewness, kurtosis and p-value of the Jarque-Bera test of all estimated structural shocks in the non-recursive SVAR estimation in section 4.4.2.

by the p-values of the Jarque-Bera test, only for the structural inflation shock ε^π Gaussianity cannot be rejected. Of course the results here depend on the assumption that the structural shocks are correctly identified, thus that sufficient non-Gaussianity is present within the true structural shocks. Hence, the results here can only serve as a first hint, if the underlying assumptions hold and should only be taken with a grain of salt. However, as at most one Gaussian shock is allowed for the data-driven identification approach to work, there is no evidence against taking the results of the fully data-driven approach serious and using it as a check for the recursiveness assumption concerning the first block of variables.

Table 4.6 shows the correlation between the estimated structural shocks from the non-recursive SVAR in section 4.4.2 and the reduced form shocks that we use to label the structural shocks retrieved from the fully data-driven approach. As it

Table 4.6: Correlation of reduced form and estimated structural shocks

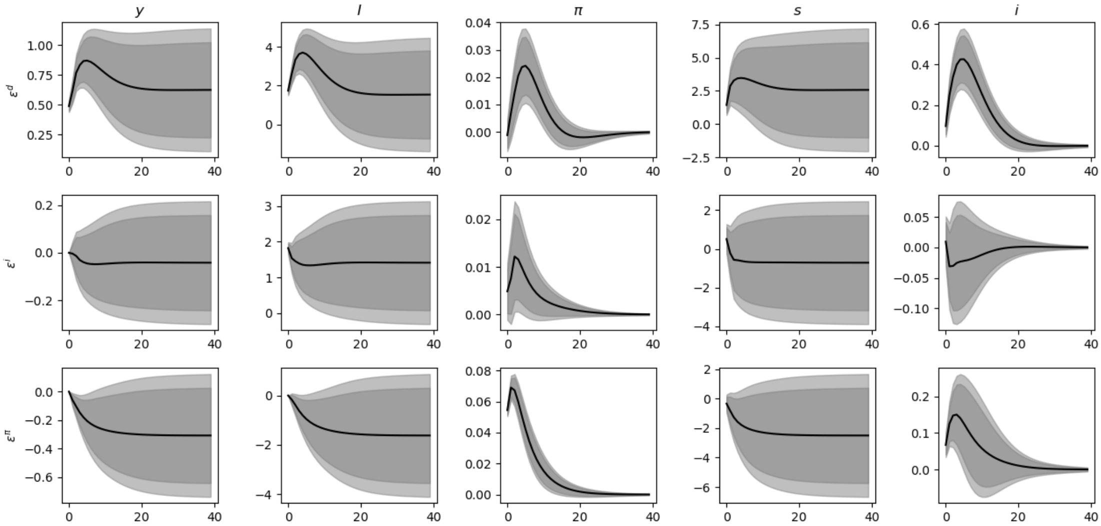
	u^y	u^I	u^π	u^s	u^i
ε^y	0.9	0.52	0.25	0.41	0.42
ε^I	0.39	0.73	-0.32	-0.35	-0.02
ε^π	-0.16	0.21	0.9	-0.23	0.15
ε^s	-0.09	0.37	-0.12	0.72	0.18
ε^i	-0.09	-0.13	-0.07	-0.37	0.88

Correlation of estimated structural shocks and reduced form shocks from section 4.4.2 .

becomes evident, the strongest correlation between reduced form errors and structural shocks is found on the main diagonal, thus we label the fourth structural shock as the stock market shock and the fifth one as the monetary policy shock.

Figure 4.4 shows the remaining set (the recursive block) of impulse responses estimated by the partly-recursive SVAR in section 4.4.2. As it becomes evident the qualitative results of the point estimates are similar to the ones regularly found in the literature. Judging by the point estimates, the qualitative results seem to be reasonable: A shock on output growth in the first row increases output and investment as well as inflation and stock prices, while the central bank will react with contractionary policy. An investment shock has no clear cut effect on output and

Figure 4.4: Remaining impulse responses estimated by the partly-recursive SVAR estimator. Responses are to structural shocks in output growth, investment growth and inflation. Confidence bands are 68% and 80% bootstrap bands. 5000 replications are used in the bootstrap algorithm. The columns y, I and s show the cumulative responses.



stock prices, leads to increasing investment an inflation, while the nominal interest rate decreases. At last, an inflationary shock induces stagflation with decreasing output, investment and stock prices, while inflation increases and the central bank pursues contractionary policy to reduce inflation. None of this seems to be unreasonable, thus we see no evidence to have doubts concerning the results found here.

We proceed by further checking on the robustness of the results presented in section 4.4. All robustness checks exploit the partly-recursive order described in equation (4.22). First we replace output growth by the growth rate in the industrial production index, which is used by Bjørnland and Leitemo (2009) due to its monthly availability, in order to see if this affects our results in any way. Table 4.7 shows the skewness, kurtosis and Jarque-Bera test results for the estimated structural shocks concerning this specification. Again, we find no evidence against at least one non-Gaussian shock in the non-recursive block. The estimated B-matrix is given by

$$\hat{B} = \begin{pmatrix} 3.26 & 0 & 0 & 0 & 0 \\ 1.25 & 1.96 & 0 & 0 & 0 \\ 0 & 0 & 0.05 & 0 & 0 \\ 2.6 & 0.16 & -0.29 & 5.32 & -1.68 \\ 0.04 & 0.05 & 0.07 & 0.09 & 0.37 \end{pmatrix}. \tag{4.50}$$

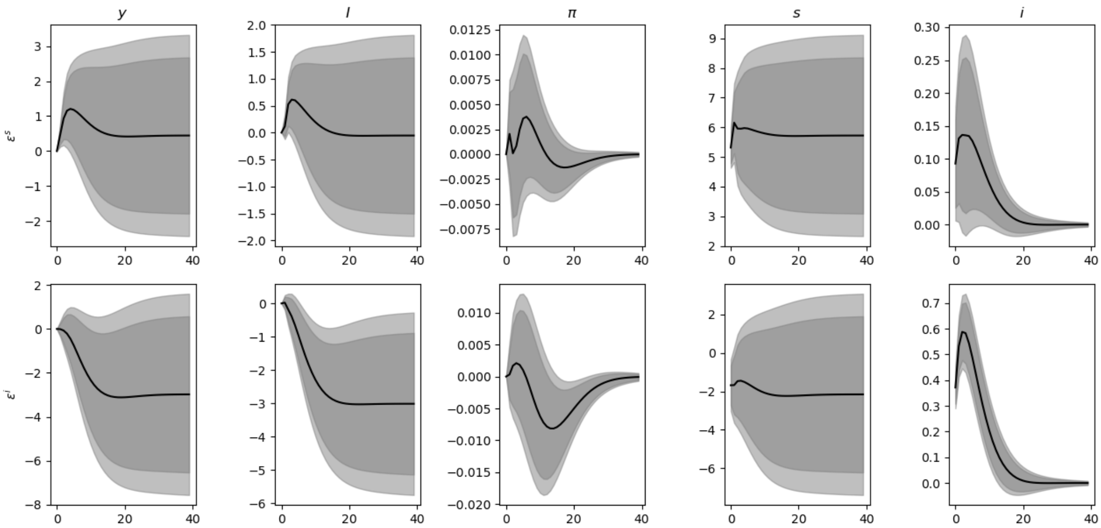
Table 4.7: Moments of estimated structural shocks (partly-recursive SVAR including the industrial production index)

	ε^s	ε^i
Skewness	-0.626	-1.102
Kurtosis	4.05	12.901
JB-Test	0.00	0.00

Skewness, kurtosis and p-value of the Jarque-Bera test of the estimated structural shocks in the second block for the specification including the industrial production index.

As it can be seen from figure 4.5, the qualitative results from our main paper are robust to this change of specification. However, now the confidence bands are a little

Figure 4.5: Impulse responses to shocks in stock returns and monetary policy with the industrial production index instead of GDPs. The columns y, I and s show the cumulative responses. Confidence bands are 68% and 80% bootstrap bands.



bit larger and the quantitative effects of monetary policy and stock market shocks a bit weaker. Nevertheless, the long-run response of stock prices to a monetary policy shock is associated with a high uncertainty. Therefore, even if the long-run neutrality of monetary policy w.r.t. stock prices holds, estimates based on long-run restrictions might be unreliable due to the volatile long-run response. In consequence, we would still favor to not be reliant on long-run restrictions.

We now check if our results are dependent on our estimation technique for the non-recursive block. Thus, we employ the PML[10] estimator proposed by Gouriéroux et al. (2017) to estimate the non-recursive block. Table 4.8 shows the estimated

[10]In contrast to our GMM based estimator that exploits the higher shock moments to construct additional moment conditions, the PML estimator relies on constructing a pseudo maximum likelihood function in order to estimate the elements of the B matrix.

higher moments for the structural stock market and monetary policy shocks. As it

Table 4.8: Moments of estimated structural shocks (partly-recursive SVAR using the PML estimator)

	ε^s	ε^i
Skewness	-0.626	-0.494
Kurtosis	4.116	14.448
JB-Test	0.00	0.00

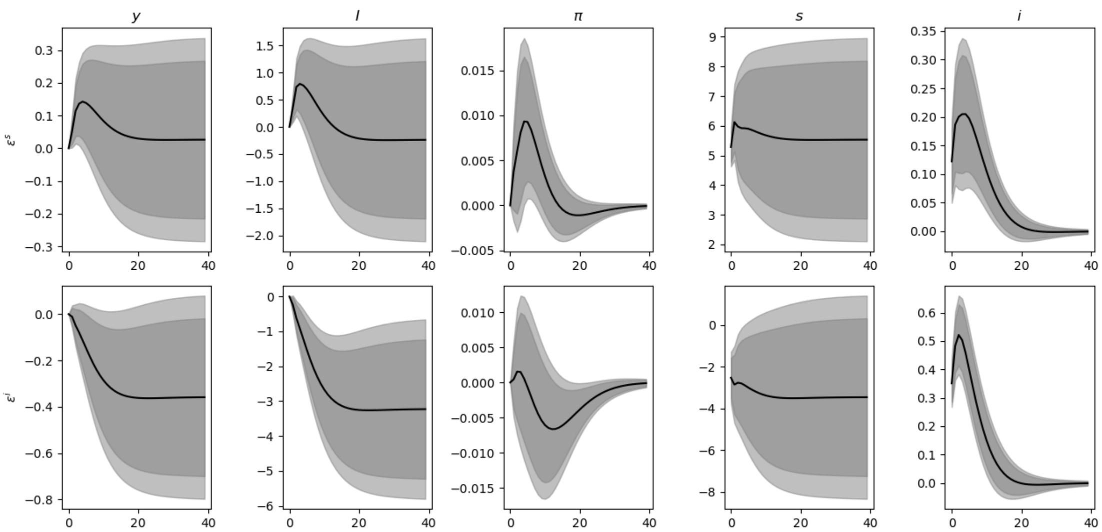
Skewness, kurtosis and p-value of the Jarque-Bera test of the estimated structural shocks in the second block for the specification using the PML estimator.

can be seen, we find evidence for both structural shocks in the non-recursive block to be non-Gaussian. The estimated B-matrix is given by

$$\hat{B} = \begin{pmatrix} 0.49 & 0 & 0 & 0 & 0 \\ 1.74 & 1.82 & 0 & 0 & 0 \\ 0 & 0 & 0.05 & 0 & 0 \\ 1.44 & 0.51 & -0.34 & 5.28 & -2.53 \\ 0.1 & 0.01 & 0.07 & 0.12 & 0.35 \end{pmatrix}. \tag{4.51}$$

Figure 4.6 shows the results. As it becomes evident, the change of the estimation

Figure 4.6: Impulse responses to shocks in stock returns and monetary policy using the PML estimator (see Gouriéroux et al. (2017)) for the non-recursive part. Confidence bands are 68% and 80% bootstrap bands. The columns y, I and s show the cumulative responses.



technique does not change our results from section 4.4: The interest rate increases in response to a stock market shock and stock prices immediately decrease after a monetary policy shock and stay permanently below the level without the shock, though this finding is associated with high uncertainty.

Third, we increase the number of lags to $p = 4$. The information criterion used in the main body of the paper relies on a normality assumption for the reduced form residuals, while we need non-Gaussian shocks for the validity of our estimates, which results in also the reduced form errors to be non-Gaussian. In consequence, the assumption needed for identification meddles with the underlying assumptions of the AIC. In order to check if there is any misspecification regarding our lag structure that might possibly influence our results, we use a different lag specification as a robustness check. Table 4.9 shows the skewness, kurtosis and Jarque-Bera test results concerning the estimated structural shocks for this specification. Again,

Table 4.9: Moments of estimated structural shocks (partly-recursive SVAR including 4 lags)

	ε^s	ε^i
Skewness	-0.824	-0.396
Kurtosis	4.744	11.965
JB-Test	0.00	0.00

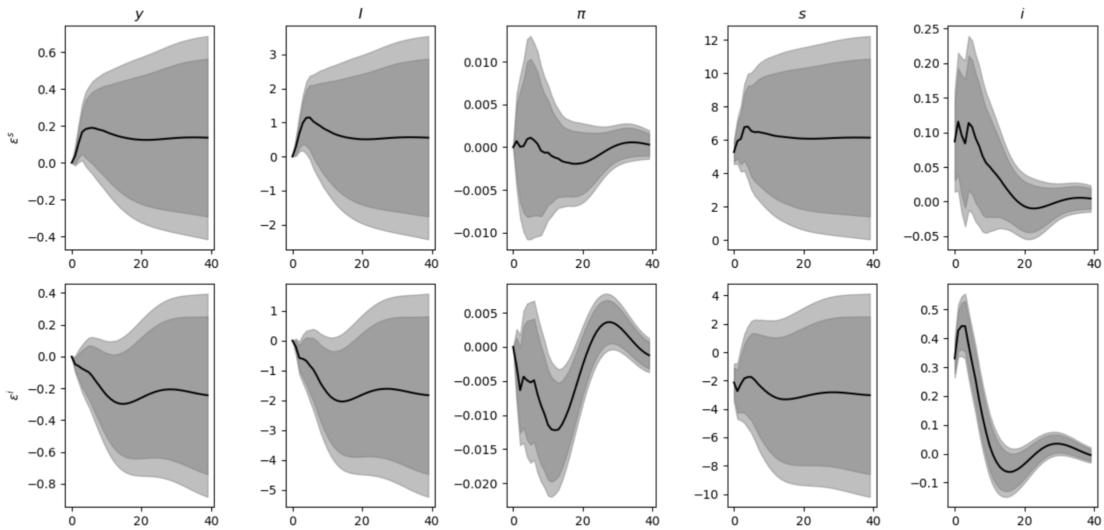
Skewness, kurtosis and p-value of the Jarque-Bera test of the estimated structural shocks from the second block for the specification including 4 lags.

we find evidence that both of the structural shocks in the non-recursive block are non-Gaussian, so the inclusion of more lags seems to not influence our identifying assumption of non-Gaussianity in the second block of variables. The estimated B-matrix is given by

$$\hat{B} = \begin{pmatrix} 0.47 & 0 & 0 & 0 & 0 \\ 1.77 & 1.64 & 0 & 0 & 0 \\ 0 & 0.01 & 0.05 & 0 & 0 \\ 1.22 & 0.66 & -0.43 & 5.27 & -2.13 \\ 0.09 & 0.04 & 0.04 & 0.09 & 0.33 \end{pmatrix}. \tag{4.52}$$

As becomes evident from Figure 4.7, the estimated simultaneous interaction is again similar to our baseline specification. However, the confidence bands in this case are quite broad and there is not much to conclude from the impulse response of stock prices to a monetary policy shock regarding the long-run behavior. Consequently, we cannot reject the long-run neutrality of monetary policy with respect to stock prices, but on the other side there is not much evidence for it either, as due to the broad confidence bands many other long-run outcomes are possible. As mentioned

Figure 4.7: Impulse responses to shocks in stock returns and monetary policy with a lag order of $p = 4$. Confidence bands are 68% and 80% bootstrap bands. The columns y, I and s show the cumulative responses.



above, we still would rather like to be not reliant on the correctness of a long-run zero restriction.

Fourth, we consider the inclusion of commodity price inflation (named πc), defined as the logarithmic difference in the producer price index (also taken from the FRED). For instance, Bjørnland and Leitemo (2009) argue that the inclusion of commodity price inflation helps to reduce the price puzzle and thus should be included into the SVAR specification. We assume that commodity price inflation shocks can be identified recursively and are ordered third in the recursive block, so commodity price inflation can react immediately to real output growth and investment growth, but not to inflation, stock market and monetary policy shocks. Table 4.10 shows the skewness, kurtosis and Jarque-Bera test results for the estimated structural shocks in this specification, where we find strong evidence for both structural shocks in the non-recursive block to be non-Gaussian. The esti-

Table 4.10: Moments of estimated structural shocks (partly-recursive SVAR including commodity prices)

	ε^s	ε^i
Skewness	-0.573	-0.755
Kurtosis	3.982	13.75
JB-Test	0.001	0.00

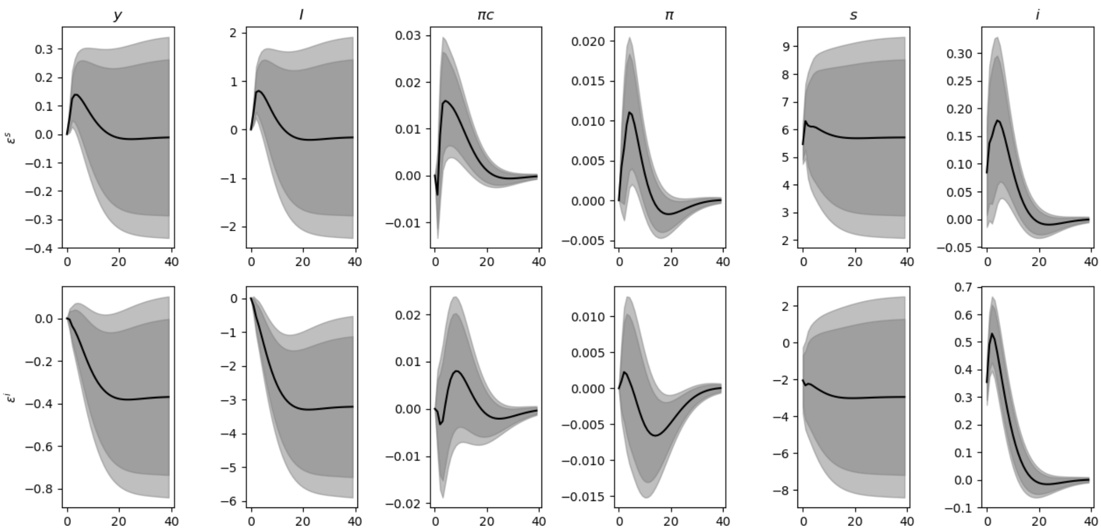
Skewness, kurtosis and p-value of the Jarque-Bera test of the estimated structural shocks from the second block for the specification including commodity prices.

mated B-matrix is given by

$$\hat{B} = \begin{pmatrix} 0.48 & 0 & 0 & 0 & 0 & 0 \\ 1.71 & 1.8 & 0 & 0 & 0 & 0 \\ -0.02 & 0 & 0.09 & 0 & 0 & 0 \\ 0 & 0.01 & 0.01 & 0.05 & 0 & 0 \\ 1.48 & 0.48 & -0.33 & -0.29 & 5.47 & -2.05 \\ 0.11 & 0.02 & 0 & 0.06 & 0.08 & 0.35 \end{pmatrix}. \tag{4.53}$$

Figure 4.8 shows the resulting IRFs. As it can be seen, the inclusion of commodity

Figure 4.8: Impulse responses to shocks in stock returns and monetary policy. Confidence bands are 68% and 80% bootstrap bands. In addition to the price level, real output growth rate, stock returns and nominal interest rate, the commodity price inflation is included. The commodity price inflation shock is identified recursively, where commodity price inflation is ordered third in the recursive block. The columns y, I and s show the cumulative responses.



price inflation has no impact on the estimated interaction of monetary policy and stock markets compared to section 4.4 and thus we omit commodity price inflation from the main paper's specification. The long-run neutrality of monetary policy shocks with respect to real stock prices cannot be rejected based on the confidence bands, but is only at the outer boundary of it, so we again conclude that we cannot for sure reject it and the evidence in favor of it is quite weak.

Fifth, we exclude all observation from 2007Q4 onward from the sample to have a similar observation period as Bjørnland and Leitemo (2009) and Kontonikas and Zekaite (2018). They exclude the observations from 2007Q4 onward in order to exclude the observations during the Great Recession, as it might potentially meddle with the underlying mechanism between monetary policy and stock markets. On the other side one could argue that the Great Recession observations might include additional information about this relationship that should not be disregarded, which is why we include also the more recent observations in our main application. Table 4.11 shows the skewness, kurtosis and Jarque-Bera test results concerning the estimated structural shocks for this specification. We find strong

Table 4.11: Moments of estimated structural shocks (partly-recursive SVAR excluding the Great Recession)

	ε^s	ε^i
Skewness	-0.67	-2.061
Kurtosis	4.478	12.97
JB-Test	0.00	0.00

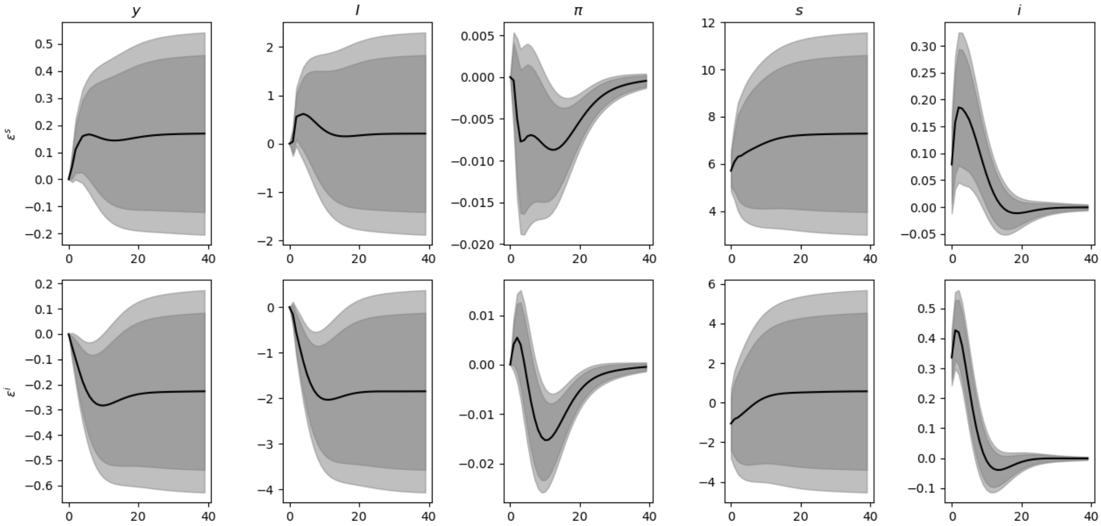
Skewness, kurtosis and p-value of the Jarque-Bera test of the estimated structural shocks from the second block for the specification excluding the Great Recession.

evidence for both structural shock in the non-recursive block to be non-Gaussian. The estimated B-matrix is given by

$$\hat{B} = \begin{pmatrix} 0.44 & 0 & 0 & 0 & 0 \\ 1.54 & 1.74 & 0 & 0 & 0 \\ -0.01 & 0 & 0.04 & 0 & 0 \\ 1.25 & 0.18 & -0.82 & 5.71 & -1.06 \\ 0.09 & 0.05 & 0.06 & 0.08 & 0.34 \end{pmatrix}. \tag{4.54}$$

Figure 4.9 shows the resulting IRFs. As it can be seen from Figure 4.9, our main results remain unchanged. The only difference is that now the response of stock prices to a monetary policy shock is not negative in the long run, but turns out to be slightly positive after about 10 quarters. In the time period that Bjørnland and Leitemo (2009) and Kontonikas and Zekaite (2018) use, the estimation hints that long-run neutrality of monetary policy with respect to stock prices seem to be more valid than in our extended sample. So for specific time frames, maybe especially during the great moderation period, monetary policy might be estimated to be neutral in the long run. However, choosing a suitable time-frame that justifies the usage of a long-run restriction seems not to be the best solution for the problem at hand, if an estimator is available that does not need the commitment to such a restriction and allows for more flexibility concerning the observation period of interest. Furthermore, the finding above again is associated with a large confidence band making the response insignificant in total judging by the 68% and 80% con-

Figure 4.9: Impulse responses to shocks in stock returns and monetary policy. Confidence bands are 68% and 80% bootstrap bands. In contrast to section 4.4 the observation period is restricted to 1983Q1-2007Q3. The columns y, I and s show the cumulative responses.



fidence bands. Long-run neutrality is part of the confidence band, but only one of several outcomes, so its validity remains unclear.

At last, we check on the relevance of the time trend included in our specification. We included a linear time trend to account for a potential drift in the nominal interest rate as noted by Carvalho et al. (2016). Here we exclude the linear time trend from the estimation procedure and assume that the nominal interest rate is stationary like in standard economic theory. Table 4.12 shows the skewness, kurtosis and Jarque-Bera test results concerning the estimated structural shocks for the specification excluding the linear time trend, where we again find strong evidence for non-Gaussianity in both estimated structural shocks in the non-recursive block.

Table 4.12: Moments of estimated structural shocks (partly-recursive SVAR excluding the time trend)

	ε^s	ε^i
Skewness	-0.548	-0.591
Kurtosis	4.025	14.851
JB-Test	0.001	0.00

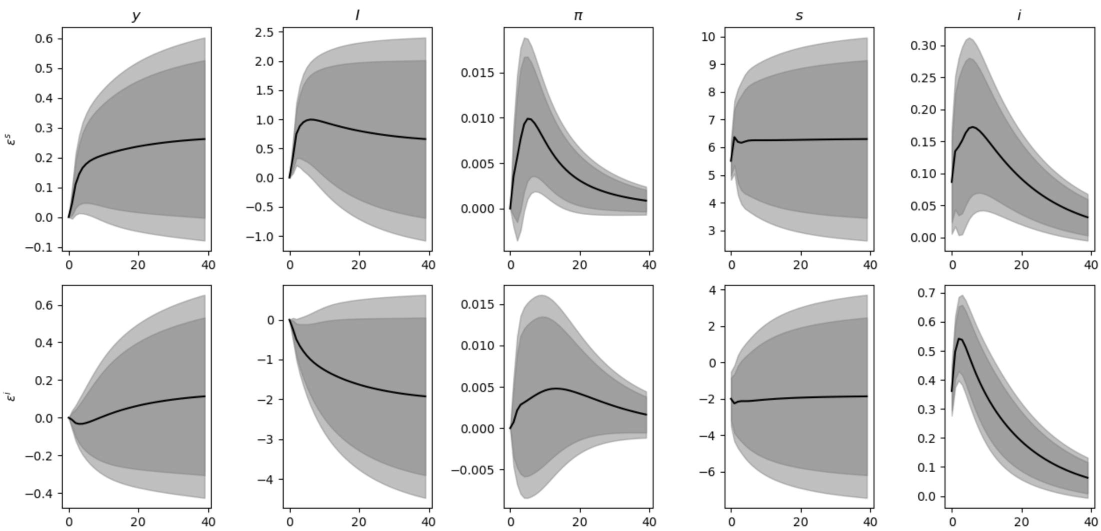
Skewness, kurtosis and p-value of the Jarque-Bera test of the estimated structural shocks from the second block for the specification excluding the time trend.

The estimated B-matrix is given by

$$\hat{B} = \begin{pmatrix} 0.5 & 0 & 0 & 0 & 0 \\ 1.81 & 1.83 & 0 & 0 & 0 \\ 0 & 0 & 0.05 & 0 & 0 \\ 1.44 & 0.5 & -0.35 & 5.51 & -2 \\ 0.1 & 0.01 & 0.07 & 0.09 & 0.36 \end{pmatrix}. \tag{4.55}$$

Figure 4.10 shows the impulse responses of the stock price and FFR to a stock market and monetary policy shock under the specification without a linear time trend. As it turns out, the main qualitative and quantitative insights remain unchanged.

Figure 4.10: Impulse responses to shocks in stock returns and monetary policy. Confidence bands are 68% and 80% bootstrap bands. In contrast to section 4.4 the linear time trend is omitted from the specification. The columns y, I and s show the cumulative responses.



However, the confidence band of the stock price response to a monetary policy shock is a bit broader, thus the response becomes insignificant earlier and there is no conclusive answer about the long-run behavior. Furthermore, the output answer becomes positive in the long run, which is something one would not expect after a contractionary monetary policy shock. As the time trend seems to contribute to a more precise and theoretically sensible estimate, we choose to leave it in our base specification.

To summarize the results from our robustness checks, we find that no matter what we do

i) the on impact effect of a monetary policy shock on stock returns is robustly negative and

ii) the on impact effect of a stock market shock on the FFR is robustly positive.

Regarding the long-run effect of monetary policy shocks w.r.t. stock prices, we find mixed evidence. In most cases the response is persistently negative, but a long-run zero effect is oftentimes just within the confidence bands. In one case, we even find a long-run positive effect, which however is small and insignificant, depending on a particular observation period and associated with a broad confidence band. Thus, we conclude that our robustness checks solidify our distrust against short- or long-run restrictions for the matter at hand and let us favor our approach compared to such restrictions.

5 How news and noise affect technological progress

5.1 Introduction

In the macroeconomic literature there has been a long-lasting interest in expectation driven business cycles, especially after the seminal paper of Beaudry and Portier (2006), who argue that information concerning news shocks to expectations about the future are incorporated within stock prices. Moreover, Lorenzoni (2009), Barsky and Sims (2012), Blanchard et al. (2013) or L'Huillier and Yoo (2017) find that even if the news later turns out to be just noise, there is a contemporaneous effect on the short-run business cycle. However, for example Blanchard et al. (2013) point to the problem that traditional SVAR techniques are not suitable to simultaneously identify news and noise shocks, as the theory predicts a singularity problem, if only one signal containing both news and noise is observed and thus the number of structural shocks exceeds the number of linearly independent variables observed by the economic agents. In particular, this means a variable is missing that contains at least partial information about the truth of the news. Consequently, the related literature mentioned above avoids SVAR approaches and mainly relies on structural models to simultaneously explore the effect of news and noise shocks. Employing fully-fledged DSGE models for the analysis, however, means that one needs to commit to the assumptions of the model. Thus, there is a lack of a more agnostic approach to empirically test the theoretical implications without imposing them on the data.

The present paper argues that the singularity problem of the SVAR can be solved, if research spending is considered as an additional variable, which is argued to provide just the necessary information to simultaneously identify news and noise shocks in an SVAR. As in Comin et al. (2009) and Kung and Schmid (2015), news shocks are interpreted as the expectation that the size of the future productivity increase in consequence of research spending today is higher than usual, thus expected productivity and stock prices increase. To additionally identify noise shocks apart from news and solve the singularity problem discussed by Blanchard et al. (2013), it is here assumed that firms directly engaging in research and in consequence being closer to the source of news, have at least a partial insight about the truth of the news and thus have an informational advantage, while firms farther away from the innovation process do not. Consequently, research spending should contain less noise than other forward looking variables like for instance stock prices. If this holds true, there are two linearly independent observables containing information about news and noise, there is no singularity problem and SVARs are a viable instrument for the analysis of news and noise shocks. The testable implication is that research spending should respond more cautiously to a noise shock than stock prices do. Later on, an SVAR containing stock prices and research spending is estimated using a recently developed data-driven identification approach, which allows to abstain from the usage of theoretical restrictions to identify the SVAR, and indeed it turns out that research spending has a, in comparison to a true news shock, much weaker response to a noise shock that induces the same stock price boom as a news shock.

This paper provides a stylized model to show the deeper reasoning, why research spending includes the information that enables the econometrician to tell apart news from noise shocks in the SVAR. In particular, it is assumed that intermediate firms are the ones to engage in research. Every period they can decide how much they want to spend on innovation and after they acquire newly researched ideas, these have to be adopted before they actually increase productivity. In each period, the intermediates receive a signal about the quality of the new ideas, where better ideas increase future productivity after adoption more than worse ones such that research investment has a higher payoff. Ex ante, the signal can contain true news and noise. However, the technology adoption is modeled as a diffusion process, where at least a small part of the ideas becomes accessible immediately to the intermediate firms. A part of the quality of the ideas is thereby revealed to the early adopting intermediaries and they get at least partial information about the truth of the news they received. If the partial information that intermediate firms get support the truth of the news, intermediate firms will invest more into the new technologies, otherwise they will act more cautiously and reduce their innovation spending. Intermediate firms sell their products to wholesalers, who sell their products to stock corporations. Thus, the stock corporations are assumed to be farther away from the research process than the intermediate firms. In consequence, they get the partial information reveal about the truth of the news slower, so on impact they have less information than researchers do.

Consequently, a noise shock that leads to the same stock price boom as a news shock should induce a more cautious response in research spending compared to a true news shock, as researchers do not fully share the optimism at the stock market. Furthermore, if the news is true, the exogenous effect on R&D productivity materializes and the effect on TFP should be stronger than after a noise shock without the direct effect, which is in line with the findings of Hirose and Kurozumi

(2021). These two theoretical results provide testable implications that can be used to evaluate if the results from the SVAR estimation are fitting. Additionally, it is assumed that neither news nor noise shocks should have an immediate influence on TFP, but that both are likely to show up immediately in stock prices and R&D spending. If the news is true, expectations are met and there is a longer-run positive increase in research spending and stock prices. If the news turns out to be just noise, the economic agents were overconfident in the new technologies and the effect on stock prices and TFP is similar, but weaker in comparison.

In order to check if the SVAR containing TFP, stock prices and research spending is able to identify news and noise shocks, a most recently developed data-driven SVAR identification method that does not rely on any theoretical restrictions is used to identify these two shocks. Thus, the model implications can be checked without imposing them on the data. Lanne et al. (2017), Gouriéroux et al. (2017), Guay (2021), Lanne and Luoto (2021) or Keweloh (2019) propose that shock identification within SVARs can be based on moments beyond the variance, if at least $n-1$ of the n structural shocks identified this way are independent and non-Gaussian. The finance literature provides much evidence that financial shocks are likely to be non-Gaussian (see for instance Mittnik et al. (2000) or Kim and White (2004)), so if Beaudry and Portier (2006) are right and stock prices do contain information about news shocks, there is a case for using the data-driven identification approach for the issue at hand. Indeed the resulting impulse responses to the news and noise shock identified by the identification approach depending on higher moments match the theoretical assumptions: Both shocks show an increase in stock prices and research spending, while the noise shock shows a comparably weaker effect on TFP and stock prices. The identified news shock has the same properties as in Beaudry and Portier (2006), so it has an immediate and persistent longer-run positive effect on stock prices and TFP, which shows that the proposed approach is able to identify a news shocks similar to the related literature. Moreover, for the noise shock the response of research spending is much weaker if the shocks are normalized to feature the same impact on stock prices like the news shock, supporting the assumption that researchers might have additional information about the truth of the news compared to the stock market. Interestingly, both shocks lead to an increase in TFP, at least in the short run. As noise shocks have no actual exogenous effect on research productivity, the observed response of TFP has to be an endogenous reaction to the expectation of higher productivity. The literature about news and noise shocks commonly assumes TFP to be entirely exogenous, the findings in the present paper, however, indicate that this assumption might not be reasonable in this case and shrouds important dynamics in productivity.

The present paper is closely related to Comin et al. (2009) and Kung and Schmid (2015), who interpret research related shocks as news shocks, due to their effect only falling into place in the medium run due to necessary technology adoption beforehand. Furthermore, it is close to Beaudry et al. (2011), Pavlov (2016) and Fan et al. (2016), who argue that news shocks lead to more endogenous innovation due to the firms expecting higher future productivity and, thus, having a higher incentive to invest in new technologies today. In addition to the aforementioned literature, the present paper also studies noise shocks alongside news shocks. As in Kurmann and Sims (2021) the revelation of noise is assumed to be only possible after at least some of the newly researched ideas are adopted and thus actually implemented. The present paper is also loosely related to the broader literature about technology adoption, see for example Comin and Gertler (2006), Benigno and Fornaro (2017) or Anzoategui et al. (2019), who acknowledge that short-run shocks can have longer-run implications on productivity due to only gradual technology adoption.

The remainder of the paper is organized as follows: Section 2 develops the theoretical background that is used to reason, why stock prices and R&D contain the necessary information about news and noise shocks and to find the conditions under which the impulse responses resulting from the data-driven identification approach can be interpreted as stemming from news or noise shocks. Section 3 then gives an overview about the data used in the present paper, the specification employed and the details of the identification approach that is followed here. Then section 4 summarizes the estimation results and discusses some robustness checks. Section 5 concludes.

5.2 Theoretical background

This section lays out a theoretical model featuring endogenous TFP growth under technology adoption and news and noise shocks. The model is intended to show, which variables need to be considered to identify news and noise shocks, especially that besides the previously used stock prices (see Beaudry and Portier (2006)) also research spending contains information regarding news about the future. This additional information from research spending about news and noise turns out to be crucial to simultaneously identify news and noise shocks in SVARs. Furthermore, a theoretical background is necessary if news and noise shocks are identified using a data-driven approach, as the labeling of the resulting impulse responses is non-trivial and relies on theory. The simple model proposed in this section consists of intermediate firms that engage in Schumpeterian competition for the firm with the highest productivity and stock corporations that benefit from higher productivity in the intermediate goods sector. News shocks are interpreted as information about higher productivity gains in the future in consequence of R&D today (news shocks are thus research related as in Comin et al. (2009) or Kung and Schmid (2015)). The prospect of higher productivity in the future due to positive news increases the competitive pressure on the intermediaries such that their research spending increases. Intermediate firms sell their products to wholesalers and wholesalers sell their products to stock corporations. Increasing productivity yields lower marginal production costs for intermediate firms and thus a lower price for the inputs of wholesalers and stock corporations, thus news about the future productivity in the intermediate goods sector ultimately affect the stock market as well. For instance a positive news shock increases expected dividends for the stock corporations such that stock prices increase. However, if the positive news shock turns out to be wrong and just noise, there is no direct exogenous effect on productivity growth and the increase in TFP is lower than after a true news shock. Furthermore, in order to solve the singularity problem discussed by Blanchard et al. (2013)[1], it is assumed that in contrast to other economic agents, researchers have at least partial information if the news is true or not. Thus, researchers will be more cautious after a noise shock than after a news shock. This information asymmetry between economic agents arises, because news shocks are like in Kurmann and Sims (2021) assumed to be revealed successively during technology adoption and firms actually performing technology adoption get these information first hand, thus they have an initial informational advantage compared to stock corporations, who are farther away from the research process and receive this information slower.

5.2.1 Intermediate firms

There is a continuum of infinitely many monopolistically competitive intermediate firms with mass one. Each intermediate firm i employs labor $N_{i,t}$ at real wage W_t and can spend $R_{i,t}$ units on the purchase of newly researched ideas with a fixed price of one (so research spending $R_{i,t}$ also coincides with the purchased number of newly researched unadopted ideas). The intermediate firms produce intermediate goods

[1]For further details on the argument in Blanchard et al. (2013) and how research spending can help to solve the singularity problem see the appendix.

$y^I_{i,t}$ and sell them at price $p^I_{i,t}$ to the wholesale sector. Consequently, intermediate firm profits read

$$\Pi_{i,t} = p^I_{i,t} y^I_{i,t} - W_t N_{i,t} - R_{i,t}. \tag{5.1}$$

Assume a simple production function linear in labor of the form

$$y^I_{i,t} = q_{i,t} N_{i,t}, \tag{5.2}$$

where $q_{i,t}$ is the current TFP level of firm i.

The TFP level has two components: First, the endogenous innovation component follows a quality ladder as in Grossman and Helpman (1991), where each newly adopted technology lets the firm climb on the ladder. Second, there is an exogenous component $exp(e^q_t)$ and e^q_t is given by

$$e^q_t = \rho^q e^q_{t-1} + \varepsilon^q_t, \quad \rho^q \in (0, 1), \tag{5.3}$$

where ε^q_t is a transitory i.i.d. aggregate TFP shock. So TFP reads

$$q_{i,t} = \underbrace{\lambda^{A_{i,t}}}_{innovation} \cdot \underbrace{exp(e^q_t)}_{exogenous}, \quad \lambda > 1, \tag{5.4}$$

with λ the technology hazard rate and $A_{i,t}$ the stock of adopted technologies. Spending more on research translates into $exp(\chi_t)$ unadopted ideas, with χ_t a news component following the law of motion

$$\chi_t = \rho^\chi \chi_{t-1} + \varepsilon^\chi_t, \quad \rho^\chi \in (0, 1), \tag{5.5}$$

and ε^χ_t an i.i.d. news shock. So like in Comin et al. (2009) the news shock is a shock to the arrival of new ideas:

$$U_{i,t} = exp(\chi_t) \frac{R_{i,t}}{q_t}, \tag{5.6}$$

where $U_{i,t}$ denotes new unadopted ideas. As in Comin and Gertler (2006), Benigno and Fornaro (2017) or Anzoategui et al. (2019), unadopted technologies then gradually diffuse to adopted technologies following

$$A_{i,t+1} = \sum_{s=1}^{\infty} (1 - \phi^s) U_{t-s+1} - \delta^A A_{i,t}, \quad \phi \in (0, 1), \delta^A \in (0, 1), \tag{5.7}$$

with $\delta^A \in (0, 1)$ an exogenous obsolescence rate of ideas. However, it is assumed that incoming news shocks are noisy and intermediate firms like in Blanchard et al. (2013) or L'Huillier and Yoo (2017) do not directly observe the news, but rather a signal ξ_t^I

$$\xi_t^I = \chi_t + \theta_t, \tag{5.8}$$

with

$$\theta_t = \rho^\theta \theta_{t-1} + \varepsilon_t^\theta, \quad \rho^\theta \in (0,1) \tag{5.9}$$

and ε_t^θ an i.i.d. noise shock. As in Kurmann and Sims (2021) the veracity of the news indicated by the signal ξ_t^I is gradually revealed during technology adoption, because some of the new technologies get adopted and the productivity increase can directly be observed. In contrast to the actual stock of adopted technologies tomorrow (5.7), the expectation about it reads (with inserting the definition for unadopted ideas (5.6))

$$E_t^I A_{i,t+1} = \sum_{s=1}^{\infty} (1-\phi^s) exp((1-\omega^s)\chi_{t-s+1} + \omega^s \xi_{t-s+1}^I) \frac{R_{t-s+1}}{q_{t-s+1}} - \delta^A A_{i,t}, \quad \omega \in (0,1), \tag{5.10}$$

where E_t^I denotes expectations of the intermediate firms, as an informational advantage about the truth of the news is assumed to be exclusive to them on impact, so they have a different information set concerning their expectations than other economic agents (the information about the truth of news arrives slower in the rest of the economy than for the intermediaries, as all other sectors are farther away from the adoption process), and ω determines the speed of the information reveal.

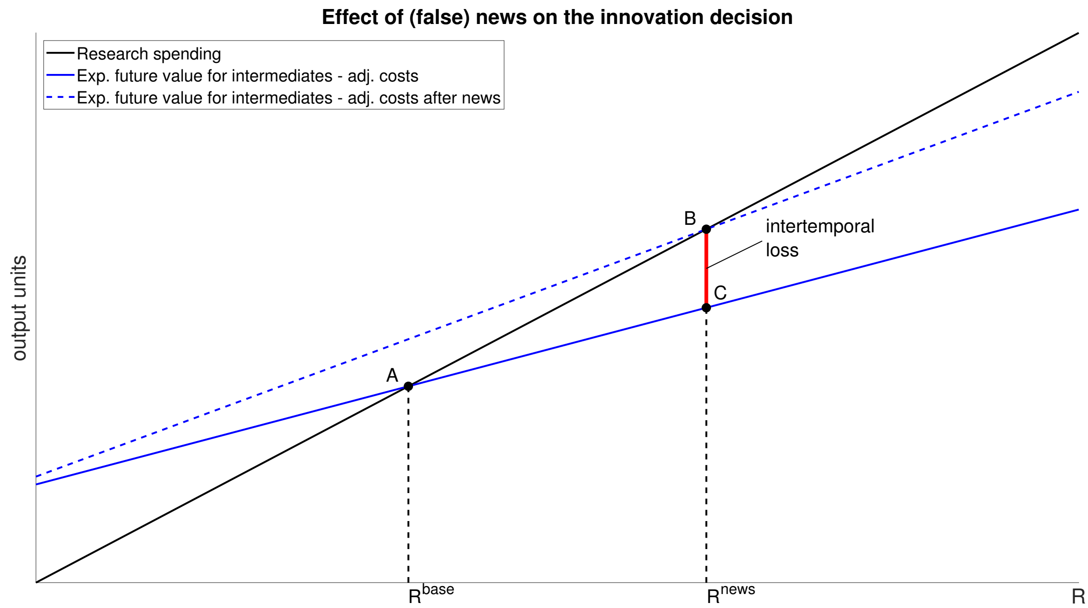
Intermediate firms are in Schumpeterian competition for their position in the market. Every period, they can decide to invest in new technologies or leave the market. Competitors that want to overtake firm i's position can costlessly imitate the current technological state, but have to acquire a higher productivity level than firm i through innovation. Consequently, in order to stay in the market, firm i has to at least invest the expected discounted future gain of being the incumbent in research to fend off the competitors' attempts to overtake its market position. At this point, competitors have zero incentive to overtake i's market position. Will firm i invest more in future productivity at this point? The answer is no. Both, competitors and firm i, will choose research spending equal to the discounted future gain of being the incumbent. If the existence of a unique interior optimum is assumed, increasing research spending at this point leads to the discounted value of being the incumbent in the future to be lower than research spending (otherwise incumbent and competitors would keep on increasing research spending). In consequence, the condition for research spending can be written as

$$R_{i,t} \stackrel{!}{=} E_t^I \Lambda_{t,t+1} \left(p^I_{i,t+1} y^I_{i,t+1} - W_{t+1} N_{i,t+1} \right), \tag{5.11}$$

so optimal research spending equals the expected discounted future sales revenue of the incumbents. On the balanced growth path, the identity of the winning firm is not affecting the optimal research decision and both, incumbents and their competitors, would choose research spending to be equal to the discounted future value of being the incumbent.

For example, figure 5.1 schematically shows what happens to research spending under positive news and noise. The solid blue line shows the expected future value

Figure 5.1: Schematic depiction of the innovation decision with and without positive news. At point A is the intersection point between research spending and expected future value of staying in the market for the intermediaries without a news shock, at point B the intersection point under a positive news shock. The intersection points mark the research spending decision for both cases. If the news turn out to be just noise, the red line between points B and C depicts the intertemporal loss due to overconfidence in the new technologies.



of winning the innovation contest in dependence of today's research spending. The black 45° line depicts the respective costs of participating in the innovation contest. The intersection point A between the two lines marks the steady state research spending without any shocks. The dashed blue line shows the expected future value of competing in the innovation contest with respect to today's research spending under positive news. Positive news is the belief that research spending leads to higher productivity gains in the future, so the dashed blue line has a higher slope than the solid one. Consequently, the intersection point B between the dashed blue line and black line is farther to the right and research spending increases. However, if the news turns out to be just noise, there is a gap between research spending and the actual future value of being in the market, as the gain curve never truly changed, and the red line between points B and C depicts the intertemporal loss incurred by the overconfidence in the new technologies. So in contrast to a positive news shock that induces a positive increase in the exogenous research productivity and thus TFP, the lack of an increase in exogenous research productivity after a noise shock leads to a lower effect on TFP than after a news shock.

Profit maximization with respect to the pricing choice of the intermediate goods firms then yields the usual result that the intermediate goods price will be a markup on the marginal production costs

$$p_{i,t}^{I} = \mu^{I} \frac{W_t}{q_{i,t}}, \quad \mu^{I} > 1, \tag{5.12}$$

where μ^I is the markup parameter.

5.2.2 Wholesaler and stock corporations

It is assumed that all other economic agents have, contemporaneously, less information about eventual noise shocks, as they are farther away from the innovation process, thus their expectation about future adopted technologies in contrast to (5.10) reads

$$E_t A_{i,t+1} = \sum_{s=1}^{\infty} (1-\phi^s) exp((1-\hat{\omega}^s)\chi_{t-s+1} + \hat{\omega}^s \xi_{t-s+1}^{I}) \frac{R_{t-s+1}}{q_{t-s+1}} - \delta^A A_{i,t}, \quad \hat{\omega} \in (0,1] \tag{5.13}$$

The important assumption is that $\hat{\omega} > \omega$, so the fraction of noise in the information set of intermediate firms is lower than in the information set of the rest of the economy. This informational advantage of intermediaries allows to discriminate news and noise shocks in an SVAR. Blanchard et al. (2013) assume $\hat{\omega} = 1$, so news and noise do have the exact same effect on stock prices and cannot be discerned from each other. Even if that holds true, an SVAR is applicable if $\omega < \hat{\omega}$ and both shocks have a different effect at least on research spending.

Wholesale output y_t^w is a CES aggregate of intermediate goods

$$y_t^w = \left[\int_0^1 \left(y_{i,t}^I \right)^{\frac{1}{\mu^I}} di \right]^{\mu^I} \tag{5.14}$$

and is used by stock corporations to produce final output goods. The wholesale price p_t^w is defined as

$$p_t^w = \left[\int_0^1 \left(p_{i,t}^I \right)^{-\frac{1}{\mu^I - 1}} di \right]^{-(\mu^I - 1)}. \tag{5.15}$$

There are infinitely many monopolistically competitive stock corporations with mass one, who buy wholesale output, costlessly differentiate it (so $y_{j,t}^S = y_{j,t}^w$) and sell resulting stock corporation output $y_{j,t}^S$ to final output users. As usual the price for the output of each stock corporation $p_{j,t}^S$ is a markup on the marginal production costs

$$p_{j,t}^S = \mu^S p_t^w, \quad \mu^S > 1, \tag{5.16}$$

where μ^S is the markup parameter for the stock corporations. Consequently, dividends for each stock corporation read

$$d_{j,t} = p_{j,t}^S y_{j,t}^S - p_t^w y_{j,t}^w = (\mu^S - 1) y_{j,t}^w. \tag{5.17}$$

Final output then is a CES aggregate of stock corporation output:

$$Y_t = \left[\int_0^1 \left(y_{j,t}^S \right)^{\frac{1}{\mu^S}} dj \right]^{\mu^s}. \tag{5.18}$$

5.2.3 Labor supply and stock price

To close the model and derive some key equations in the next section, assume a standard CES utility function for the households. Assume further a constant labor supply $N_t = \bar{N}$ and that the real wage is a constant fraction of output

$$W_t = \alpha Y_t, \quad \alpha \in (0, 1). \tag{5.19}$$

The households can invest in stocks emitted by stock corporations. The respective real stock price for each stock corporation j is denoted as $\upsilon_{j,t}$ and the dividend as $d_{j,t}$. As usual, the no arbitrage condition between saving in stocks or a riskless asset with for simplicity constant interest rate r^f yields that the real stock prices are determined as the expected discounted sum of future dividends

$$\upsilon_{j,t} = E_t \sum_{s=1}^{\infty} \Lambda_{t,t+s} d_{j,t+s}, \tag{5.20}$$

where $\Lambda_{t,t+s}$ is the stochastic discount factor between periods t and $t+s$, which under the assumptions above simplifies to $\Lambda_{t,t+s} = \frac{1}{1+r^f}$.

5.2.4 The effect of news and noise on stock prices and research spending

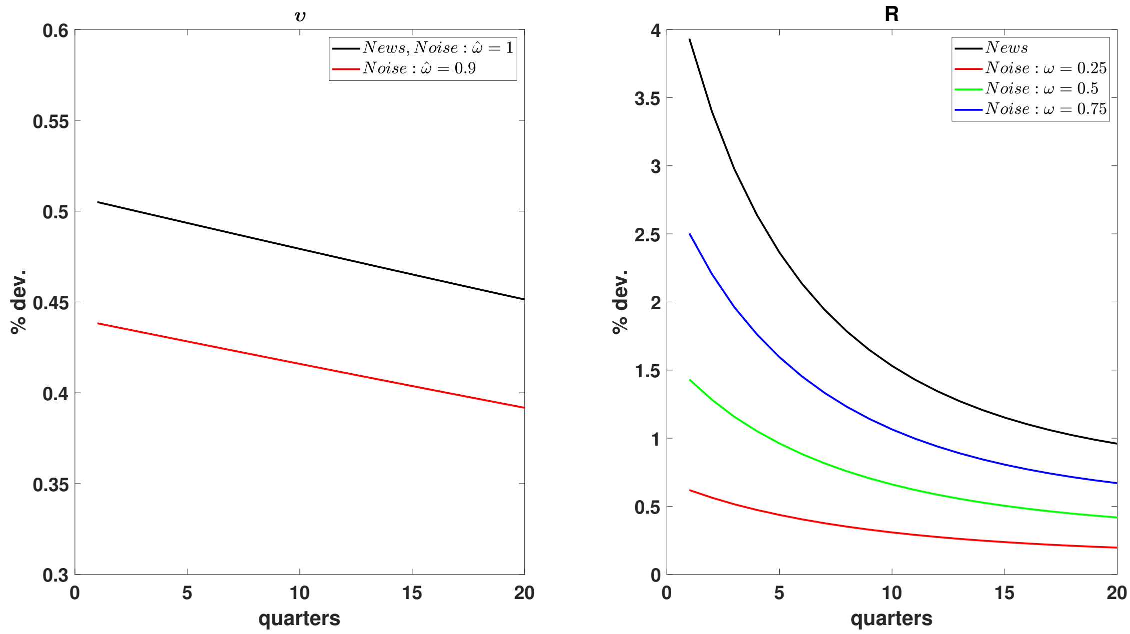
From the model above, one can conclude two equations that determine aggregate equilibrium real stock prices and research spending and are only dependent on future productivity and (constant) labor input: Assume that all intermediate firms and stock corporations are identical, then ex post by symmetry the firm indices can be dropped and using equations (5.2), (5.4), (5.11), (5.12), (5.16), (5.17), (5.19) and (5.20) the following equations result:

$$\begin{aligned} \upsilon_t &= E_t \sum_{s=1}^{\infty} \Lambda_{t,t+s} d_{t+s} = E_t \sum_{s=1}^{\infty} \Lambda_{t,t+s} (\mu^S - 1) Y_{t+s} \\ &= E_t \sum_{s=1}^{\infty} \Lambda_{t,t+s} (\mu^S - 1) \bar{N} q_{t+s} \\ &= \sum_{s=1}^{\infty} \frac{1}{(1+r^f)^s} (\mu^S - 1) \bar{N} \lambda^{A_{t+s}} exp(e^q_{t+s}) \end{aligned} \tag{5.21}$$

$$\begin{aligned} R_t &= E_t^I \left(\Lambda_{t,t+1} (\mu^I - 1) \frac{W_{t+1}}{q_{t+1}} Y_{t+1} \right) \\ &= E_t^I \left(\Lambda_{t,t+1} (\mu^I - 1) \alpha \left(\frac{Y_{t+1}}{q_{t+1}} \right) Y_{t+1} \right) \\ &= E_t^I \left(\Lambda_{t,t+1} (\mu^I - 1) \alpha \bar{N} q_{t+1} \right) \\ &= E_t^I \left(\frac{1}{1+r^f} (\mu^I - 1) \alpha \bar{N} \lambda^{A_{t+1}} exp(e^q_{t+1}) \right) \end{aligned} \tag{5.22}$$

Referring to the expectations about A_t of intermediate firms (5.10), the research spending equation (5.22) depends only on current and past research spending and the exogenous shocks, while the stock price equation (5.21) depends on current, past and future research spending and the exogenous shocks. So for a given starting value of the TFP level q_0 one can calculate the sum of past research spending that has diffused into adopted technologies and than solve for the optimal current and future research spending. From this point on, the effect of news and noise shocks can be simulated. Figure 5.2 shows the simulation[2] of the stock price and research spending reactions to a news and noise shock of size 1 for $\hat{\omega} = 1$ and $\hat{\omega} = 0.9$, as well as different values for ω.

Figure 5.2: Model simulation of stock price and research spending responses to news and noise shocks of size 1 under different values for ω and $\hat{\omega}$



As it can be seen, for $\hat{\omega} = 1$, as assumed in Blanchard et al. (2013), news and noise have the same effect on stock prices and cannot be discerned from each other without the additional information provided by research spending. Even for $\hat{\omega} = 0.9$ the difference in the impact effect of news and noise shocks on stock prices is small, while, depending on the given ω, the impact effect of a noise shock on research spending can be lower by a factor of up to 8 for $\omega = 0.25$ compared to a news shock. This visualizes, how under the assumptions of the model above research spending provides the necessary variation between the effects of news and noise shocks that allows to tell both shocks apart in an SVAR approach. What can be learned from the simulation concerning the behavior of research spending, TFP and stock prices after a news or noise shock? First, arriving news lead to an immediate increase in research spending and stock prices. Second, as news and noise both lead

[2]For the model simulation the parameters are calibrated as follows: A mean growth rate of 2% is assumed, so with household discounting $\beta = 0.998$ the interest rate $r^f = 0.022$ obtains, intermediate and stock corporation markups are set to 20%, so $\mu^S = \mu^I = 1.2$, the starting value for q_0 is set to 1.01, then $\bar{N} = 6.2148$ ensures a steady state growth rate of 2%, the labor income share $\alpha = \frac{2}{3}$, $\lambda = 1.03$ as in Basu and Fernald (1997), the adoption rate $\phi = 0.1$ as in Comin and Gertler (2006) and the technology obsolescence rate $\delta^A = 0.1$ as in Moran and Queralto (2018).

to more research spending, TFP should increase over time in both cases. However, due to the missing direct effect on exogenous research productivity and the more cautious response in research spending, the TFP effect should be lower after a noise shock than after a news shock. Third, because intermediaries are more cautious, the increase in research spending should be lower after a noise shock than after a news shock.

5.3 The empirical model

5.3.1 Data and specification

The stock price equation (5.21) and research spending equation (5.22) depend on the four variables stock prices, research spending, TFP and labor input. Thus, the baseline specification of the VAR studied here should include representatives for these four variables, specifications including additional controls are studied afterwards. This paper uses U.S. time series data between 1980q1 and 2020q1. Data on utilization adjusted TFP growth g^{TFP} is obtained from Fernald (2012-2019). The TFP level index for each date t is then calculated by imposing a starting value of 100 and multiplying it for each observation period with $\prod_0^t (1 + g_t^{TFP})$. The logarithm of the TFP level is subsequently simply denoted as TFP. The rest of the data is obtained from the FRED (2021): The real stock price is defined as the Wilshire 5000 index[3] divided by the seasonally adjusted implicit GDP price deflator, the logarithm of the real stock price is subsequently denoted as SP. Real R&D expenditures are measured as the seasonally adjusted part of GDP used for research and development divided by the GDP deflator as defined before. The logarithm of real R&D expenditures is later on simply denoted as $R\&D$. Hours worked are defined as the seasonally adjusted weekly hours worked in the manufacturing sector. The logarithm of hours worked is subsequently just called $hours$. Further variables used for robustness checks are the logarithm of seasonally adjusted gross private nonresidential intellectual property products investment divided by the GDP deflator as an alternative measure for research effort (subsequently denoted as IPI) and the logarithm of seasonally adjusted gross private domestic investment divided by the

[3]Most applications regarding news shocks use the S&P 500 index as the relevant stock price index, which includes the 500 biggest stock corporations for the United States. The Wilshire 5000, however, includes all listed stock corporations for the United States. The reasoning for favoring the Wilshire 5000 index in this paper is that news is understood as research related news and not some unspecific shock to future productivity. As research in reality most of the time affects only certain sectors and not all firms equally, a broader stock price index is more likely to catch the entirety of research related news than a narrower one.

GDP deflator as a further control variable (subsequently denoted as $Inv.$).

The baseline specification contains a constant, a linear time trend and the logarithms of TFP, hours, real stock prices and real R&D spending. A lag order of 4[4] is chosen, but different lag orders are employed in the appendix as robustness checks. So the baseline VAR specification reads

$$\begin{pmatrix} TFP_t \\ Hours_t \\ SP_t \\ R\&D_t \end{pmatrix} = \delta + \gamma t + \sum_{1}^{4} A_i \begin{pmatrix} TFP_{t-i} \\ Hours_{t-i} \\ SP_{t-i} \\ R\&D_{t-i} \end{pmatrix} + \begin{pmatrix} u_{1,t} \\ u_{2,t} \\ u_{3,t} \\ u_{4,t} \end{pmatrix}. \tag{5.23}$$

The relationship between reduced form errors u_i and structural shocks ε_i is denoted as

$$u_t = \begin{pmatrix} u_{1,t} \\ u_{2,t} \\ u_{3,t} \\ u_{4,t} \end{pmatrix} = \begin{pmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{pmatrix} \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \\ \varepsilon_{4,t} \end{pmatrix} = B\varepsilon_t. \tag{5.24}$$

The B-matrix contains 16 elements and there are 10 conditions for identification provided by the second moments, while at least 6 further identifying restrictions have to be found in order to identify the SVAR.

5.3.2 Identification

The seminal paper by Beaudry and Portier (2006) suggests that news shocks can be identified in a 2 variable setup with TFP and stock prices by imposing a zero restriction on the contemporaneous effect of news on TFP. So while the effect of news on TFP lies in the future by definition, it shows up contemporaneously in stock prices, as the stock market incorporates news about the future immediately. However, in the present paper noise shocks, which have no direct effect on endogenous productivity, are studied in addition to news shocks. Following Comin et al. (2009), true news can be interpreted as shocks to the idea production from R&D, which affect TFP only in the future because ideas need to be adopted before they increase actual productivity, while noise only affects the expectation about

[4]The lag order is chosen ad hoc here, as traditional information criteria assume normally distributed structural shocks, which collides with the identifying assumption of non-Gaussianity for at least a subset of structural shocks. However, the lag order of 3 determined by the Akaike information criterion (AIC) is used in the appendix as a robustness check.

the future productivity gain due to R&D. Consistent with the previous theoretical insights, one would thus assume that both news and noise shocks have no contemporaneous impact on TFP, but both can have a contemporaneous effect on stock prices and R&D expenditures. Because of this, the recursive identification scheme employed by Beaudry and Portier (2006) fails here, as it falls short of one identifying restriction. If the assumption of at least partial signal extraction by the intermediate firms is true, the singularity problem discussed in Blanchard et al. (2013) is solved[5], as now with research spending there is one variable observed, which provides the necessary information to discern news from noise shocks and the SVAR approach is applicable.

The missing identifying assumption in this paper is replaced by an identification scheme relying on higher moments following Lanne et al. (2017), Gouriéroux et al. (2017), Guay (2021), Lanne and Luoto (2021) or Keweloh (2019), which assumes that at most one structural shock is Gaussian, which enables to use moments beyond the variance to estimate the remaining elements of the B-matrix using GMM. As Keweloh and Seepe (2020) (the previous chapter of this dissertation) show, a major problem of fully data-driven identification approaches is that they get more imprecise the more variables are included in the SVAR and the lower the number of observations. As explained in Keweloh and Seepe (2020) (the previous chapter of this dissertation), exploiting a partly-recursive ordering can substantially improve the performance of the estimator. As the fully data-driven estimation cannot reject that news and noise shocks do not contemporaneously affect TFP and hours, the partly-recursive SVAR estimator is applied afterwards. For that matter, TFP and hours are added recursively and ordered first and second respectively, so it is assumed that TFP and hours do not contemporaneously react to news and noise shocks. As imposing the short-run restrictions for the effect of news and noise on hours and TFP improves the precision of the estimates by reducing the number of moment conditions that need to be fulfilled and makes the shock-labeling more easy. Moreover, as Keweloh and Seepe (2020) (the previous chapter of this dissertation) note, wrongly assigning zero restrictions on the interaction between the variables in the recursive block of variables does not affect the identification of the shocks in the non-recursive block, as long as the zero restrictions between both blocks hold. The approach using a partly-recursive identification is favored in the subsequent analysis regarding the robustness checks. So regarding the baseline specification mentioned above, the elements b_{12}, b_{13}, b_{14}, b_{23} and b_{24} are restricted

[5]For further details why this helps to solve the singularity problem see the appendix.

to zero, while b_{34} remains unrestricted and is estimated based on moments beyond the variance, so no further recursiveness assumption is necessary here:

$$\begin{pmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{pmatrix} = \begin{pmatrix} b_{11} & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{pmatrix} \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \end{pmatrix}. \tag{5.25}$$

Later on, investment is also added recursively and ordered first as a robustness check.

There is strong empirical evidence for excess kurtosis in the residual of estimations containing financial series such as stock prices (see for instance Mittnik et al. (2000) or Kim and White (2004)). So at least one of the structural shocks has to be non-Gaussian, as a combination of only Gaussian shocks within the residuals would lead to Gaussian residuals. To check on this assumption, the distributional properties and Jarque-Bera test results are given for every specification below. Moreover, in the appendix the PML estimator (see for instance Gouriéroux et al. (2017)) is used alternatively to check on the robustness of the results to a change of the estimator for the non-recursive block. One drawback of using the data-driven identification scheme is that the shock labeling is not trivially given by the identifying assumptions like for instance in a fully recursive identification scheme. Especially, it is ex ante unclear, which of the resulting structural shocks refers to a news and which to a noise shocks if they do at all. So it is necessary to conclude from the behavior of the impulse responses and some theoretical background, which shock is suiting respectively. From the previous theoretical deliberations, the following assumptions are used to label news and noise shocks:

(i) Both, news and noise shocks, have a positive impact on stock prices and R&D.

(ii) As noise shocks have no direct effect on TFP, the effect on TFP and stock prices should be weaker compared to the effect of a news shock.

(iii) On the other hand, as true news is directly boosting longer-run TFP, there should be a positive longer-run effect on TFP and stock prices.

(iv) The research spending response should be weaker after a noise shock compared to the response after a news shock.

So in a first step the structural shocks that are correlated the strongest with the reduced form errors u_1 and u_2, in this case ε_1 and ε_2, are considered as a labor market and TFP shock, as the structural labor market and TFP shocks should still be the main contributors to the residual in the first and second line of the reduced form VAR. For the remaining structural shocks, in this case ε_3 and ε_4, the above assumptions are used to label the news and noise shock. In the partly-recursive identification scheme, the labeling regarding the recursive block is following directly from the identifying assumptions and the criteria above suffice to label news and noise shocks in the non-recursive block.

5.4 Results

5.4.1 Fully data-driven identification

At first, this section employs an estimation of the SVAR fully relying on higher moments in order to rely on as few theoretical restrictions as possible concerning the results. This requires to have at most one Gaussian shock among the structural shocks. Table 5.1 shows the skewness, kurtosis and Jarque-Bera test results for the reduced form errors and structural shocks. As it can be seen, normality can be

Table 5.1: Skewness, kurtosis and Jarque-Bera-test results for the fully data-driven approach

Reduced form errors	u_1	u_2	u_3	u_4
Skewness	0.2951	0.0368	-0.9949	-0.2876
Kurtosis	3.4862	4.7979	6.4683	3.8206
JB-Test p-Value	0.1079	0.0025	0.0010	0.0368
Structural shocks	ε_1	ε_2	ε_3	ε_4
Skewness	0.1595	0.3029	-1.1272	-0.2266
Kurtosis	3.4789	4.8547	6.9950	3.9941
JB-Test p-Value	0.2753	0.0016	0.0010	0.0261

rejected for the reduced form errors u_2 and u_3 at the 1% level and for u_4 at the 5% level. Thus, there is evidence that there is at least one non-Gaussian structural shock. Looking at the p-values of the Jarque-Bera test for the identified structural shocks, it shows that for ε_2 and ε_3 normality can be rejected at the 1% level and for ε_4 at least at the 5% level. There is no evidence that ε_1 is non-Gaussian, however, the requirement of at most one Gaussian structural shock seems to be fulfilled.

Table 5.2 shows the correlation matrix between reduced form errors and the estimated structural shocks from the fully data-driven identification approach. As it

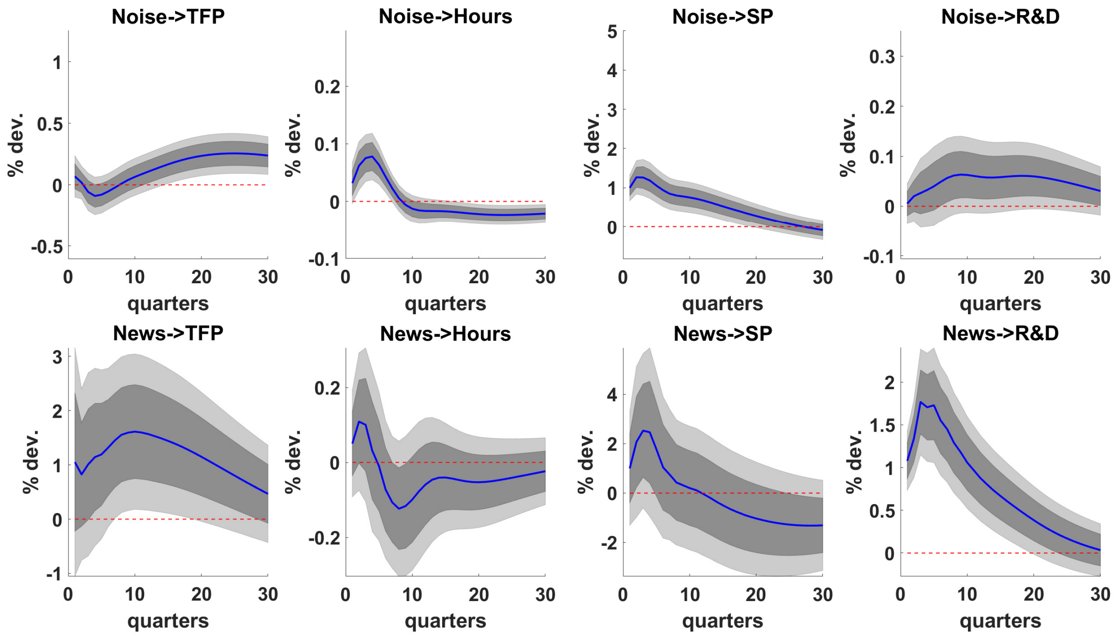
Table 5.2: Correlation matrix concerning structural shocks and reduced form errors for the fully data-driven approach concerning news and noise shocks

	ε_1	ε_2	ε_3	ε_4
u_1	0.8957	-0.1214	-0.1047	-0.2271
u_2	-0.2975	0.9038	-0.2081	-0.0366
u_3	0.1423	0.4012	0.9636	0.0345
u_4	0.2983	0.0863	0.1313	0.9726

can be seen, from the argument in the previous section the structural errors ε_3 and ε_4 seem to be the candidates for the news and noise shock, as ε_1 has the highest correlation with u_1 (so likely a labor market shock), while ε_2 has the highest correlation with u_2 of the reduced form VAR (so likely a TFP shock). Figure 5.3 shows the resulting impulse responses for the fully data-driven identification. The first and second row show the responses to structural shocks ε_3 and ε_4. As becomes evident, the peak stock price effect is weaker by a factor of about two and the TFP effect by a factor about ten in the first row. Furthermore, the response of research spending is much weaker in the first row compared to the second row. Consequently, ε_3 fulfills all the conditions from the previous section to be interpreted as the noise shock and ε_4 all the conditions to be labeled as the news shock, according to the labeling assumptions. Both shocks are normalized to have an impact effect of one on stock prices, which allows for an easier interpretation of the effect of news and noise shocks.

As becomes evident, the news shock leads to no clear effect in hours and an increase in TFP and stock prices, which coincides with the findings of Beaudry and Portier (2006), Barsky and Sims (2011) or Barsky et al. (2015), and also an increase in R&D spending, which is consistent with the theoretical deliberations in Comin et al. (2009) and this paper's modeling section. Furthermore and in line with the testable implication about news shocks, the effect on TFP and stock prices is much stronger compared to the noise shock effect. In consequence of a noise shock hours, stock prices and R&D spending increase in the short run, because firms expect a productivity boost in the future. There is an initial short-lived decrease in TFP after the noise shock hits the economy, which is not predicted by the simple model in the previous section, but might be reasoned by the overinvestment in research leading to a congestion effect (as discussed in Comin and Gertler (2006) or Anzoategui et al. (2019)) in technology adoption that initially outweighs the positive effect of more research. In the medium run TFP increases, because the overinvestment in research spending leads to a higher quantity of ideas getting

Figure 5.3: Fully data-driven identification with no contemporaneous zero restrictions imposed to identify the shocks. Impulse responses are normalized to an impact effect of one on stock prices for both, news and noise shocks. Confidence bands are 68% (darker shade) and 90% (lighter shade) bootstrap confidence bands resulting from 5000 resamplings.



adopted. As it can be seen, a noise shock that induces the same stock price reaction as a news shock only leads to a small and insignificant increase in R&D spending on impact. As the positive expectations about the future induce a business cycle boom, firms endogenously increase their research efforts afterwards, but still the effect is much weaker than after a news shock, as there is no exogenous increase in the research productivity like after a news shock and thus the marginal effect of more research is lower.

The drawback of using a fully data-driven identification approach is that, with an increasing number of variables, the precision of the estimates gets increasingly worse, so it becomes increasingly difficult to conclude any insights from the results, which makes including more control variables problematic. As becomes evident, zero is part of the confidence band for hours and TFP concerning news and noise shocks, thus there is no strong evidence that a recursiveness assumption here is wrong and imposing zero restrictions on the effect of news and noise shocks on TFP and hours is viable. As the zero impact restriction for the recursive block of variables cannot be rejected, the partly recursive, partly data-driven identification is favored for the subsequent analysis and the robustness checks.

5.4.2 Partly-recursive specification

This section examines the effect of news and noise shocks estimated by the partly-recursive SVAR estimator as proposed in Keweloh and Seepe (2020) (the previous chapter of this dissertation). Additionally, the impulse responses to a TFP shock are shown, to compare the results to the traditional approach of Beaudry and Portier (2006), who identify a news and TFP shock in a 2 variable VAR by assuming a recursive ordering of TFP and stock prices. The following figures only show the impulse responses for TFP, noise and news shocks, the full set of impulse responses for the partly-recursive specification can be found in the appendix. For the recursive block, the impact responses are normalized to one on the main diagonal, while for the non-recursive block it is assumed that both shocks have an impact effect of one on stock prices, which allows for an easier interpretation of the effect of news and noise shocks. Table 5.3 shows the skewness, kurtosis and Jarque-Bera test results for the partly-recursive specification. As it can be seen, a normal distribution can

Table 5.3: Skewness, kurtosis and Jarque-Bera-test results for the partly-recursive specification

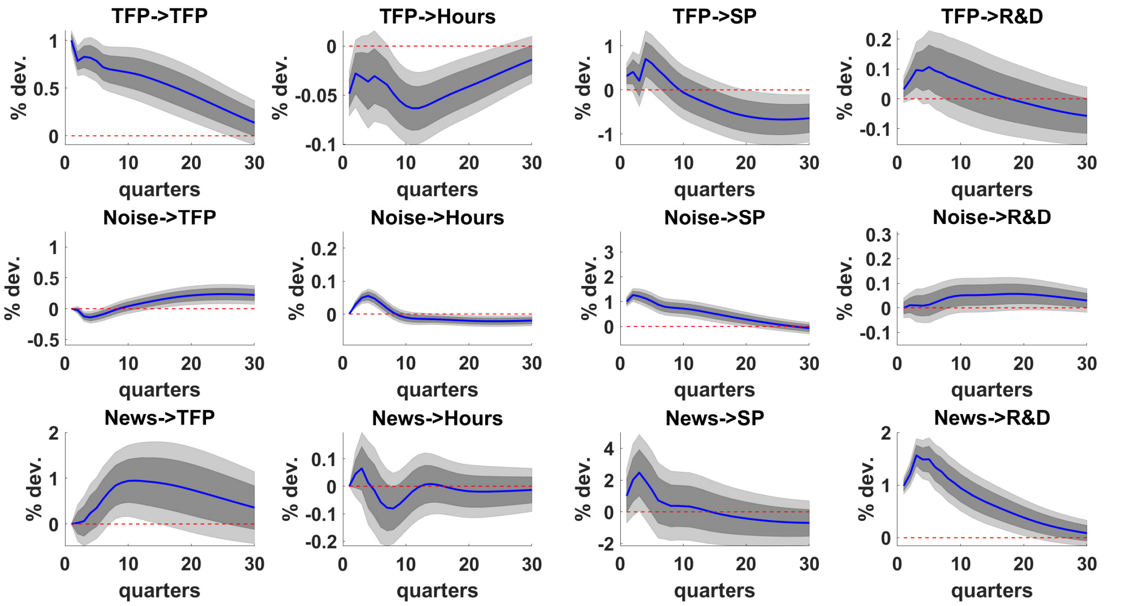
Reduced form errors	u_1	u_2	u_3	u_4
Skewness	0.2915	0.0368	-0.9949	-0.2876
Kurtosis	3.4862	4.7979	6.4683	3.8206
JB-Test p-Value	0.1079	0.0025	0.0010	0.0368
Structural shocks	ε_1	ε_2	ε_3	ε_4
Skewness	0.2915	-0.0324	-0.8252	-0.2943
Kurtosis	3.4862	4.6213	5.6978	3.4791
JB-Test p-Value	0.1079	0.0042	0.0010	0.1080

be rejected for two of the reduced form errors at the 1% level and for one at least at the 5% level. Thus, there is strong evidence that there is at least one non-Gaussian structural shock. Looking at the structural shocks identified by the SVAR, it shows that normality can be rejected for ε_3 at the 1% significance level and for ε_4 almost at the 10% level, so there is evidence that the requirement defined in Keweloh and Seepe (2020) (the previous chapter of this dissertation) of at least one structural shock in the non-recursive block being non-Gaussian is fulfilled.

Figure 5.4 shows the resulting impulse responses from the partly-recursive approach. The second and third row show the responses to structural shocks ε_3 and ε_4. Again, the peak effect on positive TFP and stock prices is much weaker in the second row than in the third row. Furthermore, the response of research spending is weaker in the second row compared to the third row. Consequently, ε_3

is interpreted as the noise shock and ε_4 is labeled as the news shock. The labeling of the TFP shock follows directly from the recursiveness assumption. As it can be

Figure 5.4: Partly-recursive specification including hours, utilization adjusted TFP, real stock prices and real R&D spending. Impulse responses are normalized to an impact effect of one on the main diagonal for the recursive variables and to an impact effect of one on stock prices for both news and noise shocks. Confidence bands are 68% (darker shade) and 90% (lighter shade) bootstrap confidence bands resulting from 5000 resamplings.



seen, the results are qualitatively and quantitatively similar to the fully data-driven approach, however the confidence bands are narrower and the impact effects are estimated with higher precision due to exploiting the recursiveness assumption and reducing the "curse of dimensionality" explained in Keweloh and Seepe (2020)(the previous chapter of this dissertation). Furthermore, the labeling of the shocks in the recursive block is now not only dependent on the correlation between reduced form errors and structural shocks, but follows from the recursiveness assumptions. This and the lower dependency on non-Gaussianity, as now there has to be at most one Gaussian structural shock only in the non-recursive block, allows for more flexibility and more precise results when introducing further control variables, which is why the partly-recursive, partly data-driven approach is favored for the subsequent analysis.

One remarkable finding in both the fully data-driven and partly-recursive estimation is that the impact effect of research spending in consequence to a noise shock is close to zero. This is not imposed as a restriction, but freely estimated. An impact effect of zero means that in terms of the model in the modeling section $\omega \approx 0$ and intermediate firms have nearly perfect information about the truth of news. This means that research spending seems to be a nearly perfect indicator for if a stock price boom is justified by true news or not. The subsequent small positive reaction of research spending is due to the increase in demand induced by the boom on the stock market, but not because researchers have faith in a future increase in research productivity.

Another interesting finding from both approaches is that the results above confirm the theoretical outcome that noise shocks, besides having no direct effect on TFP, lead to a medium-run increase in TFP. As the effect only works through expected changes that never materialize, the observed TFP effect has to come from a response in the endogenous part of TFP. The firms expect new ideas to be more productive and thus expect a higher future value of the firm. According to the model in the previous section, they respond by higher investment in new ideas to stay in the market. Thus noise shocks, despite being without any direct real effect, can affect TFP in the short to medium run. Moreover, the results confirm the assumption that research spending contains at least partial information about the truth of the news, as a noise shock that leads to the same stock price boom like the news shock, leads to a much weaker (about a factor between 10 to 20 in both the fully data-driven and partly-recursive case) response in research spending. Thus, there is evidence that the singularity problem pointed out in Blanchard et al. (2013) can be solved by using research spending as an additional variable within the SVAR.

5.4.3 Robustness checks

The main idea that allows to incorporate TFP, news and noise shocks at the same time is that, besides stock prices, also research spending incorporates information about news and noise. As research spending is notoriously hard to measure, the question stands, if the results are robust to alternative measures for it. As a robustness check, research spending is now measured as intellectual property investment of private firms. Table 5.4 shows the skewness, kurtosis and Jarque-Bera test results for the specification including IPI instead of R&D spending. As it becomes evident, in contrast to the previous specification, the reduced form error u_4 is no longer significantly non-Gaussian at the 10% level and the p-value of the Jarque-Bera-test indicates that normality cannot be rejected for the structural shock ε_4. However, there are still two reduced form errors, where normality can be rejected

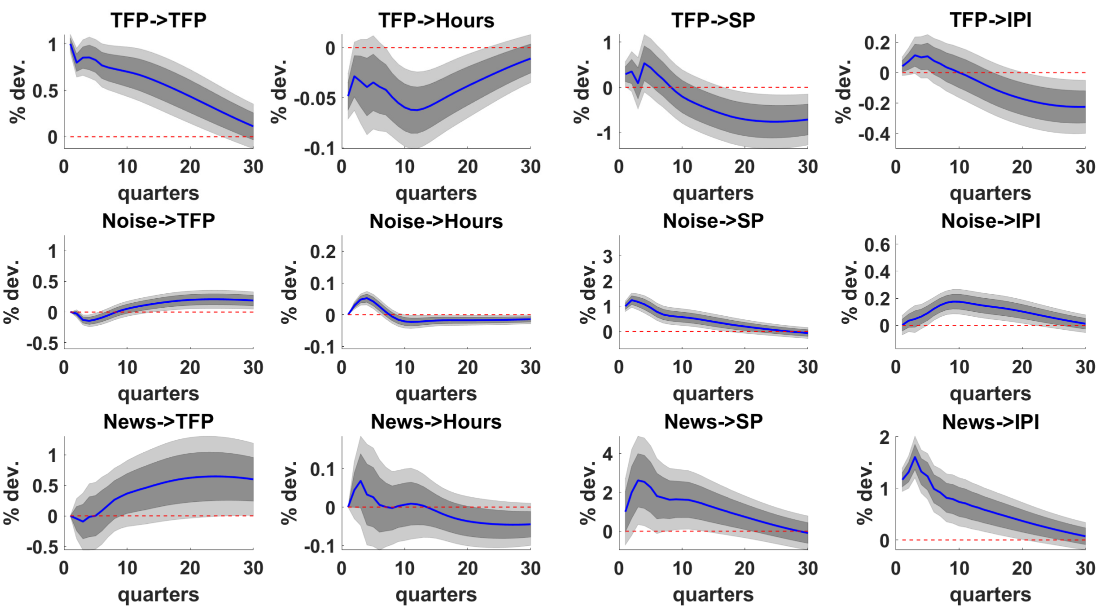
Table 5.4: Skewness, kurtosis and Jarque-Bera-test results for the specification with IPI as an alternative R&D measure

Reduced form errors	u_1	u_2	u_3	u_4
Skewness	0.2208	-0.0165	-1.1169	-0.0034
Kurtosis	3.3558	4.9136	7.0567	3.5288
JB-Test p-Value	0.2864	0.0018	0.0010	0.3373
Structural shocks	ε_1	ε_2	ε_3	ε_4
Skewness	0.2208	-0.0884	-0.9204	-0.0082
Kurtosis	3.3558	4.7584	6.0335	3.3449
JB-Test p-Value	0.2864	0.0027	0.0010	0.5000

at the 1% level, so there has to be at least one non-Gaussian structural shock. The Jarque-Bera-test for the estimated structural shock ε_3 shows that normality can be rejected at the 1% level, thus the requirement for the feasibility of the identification scheme based on higher moments for the non-recursive block seems to be fulfilled.

Figure 5.5 shows the resulting impulse responses for the specification containing IPI. The labeling of the news and noise shock is analogous to before. As it turns

Figure 5.5: Robustness check with private intellectual property investment (IPI) as an alternative R&D measure. Impulse responses are normalized to an impact effect of one on the main diagonal for the recursive variables and to an impact effect of one on stock prices for both news and noise shocks. Confidence bands are 68% (darker shade) and 90% (lighter shade) bootstrap confidence bands resulting from 5000 resamplings.



out, the results remain mainly unchanged: News shocks lead to a significant long-run increase in TFP, stock prices and R&D spending, while a noise shock has a similar, but much weaker, effect on the aforementioned variables. The main findings remain robust to the change in the R&D variable, especially that the reaction of research spending in consequence to a noise shock is much more cautious than after a news shock. Even the estimated impact effect of nearly zero is the same, which reinforces the notion of research related variables as good indicators for the truth of news.

As a further robustness check, private investment is added to check if the business cycle properties of the news and noise shock are consistent with the findings of the related literature. Investment is added recursively and ordered first. Table 5.5 shows the skewness, kurtosis and Jarque-Bera-test results of the specification including private investment. As it becomes evident, all reduced form errors are

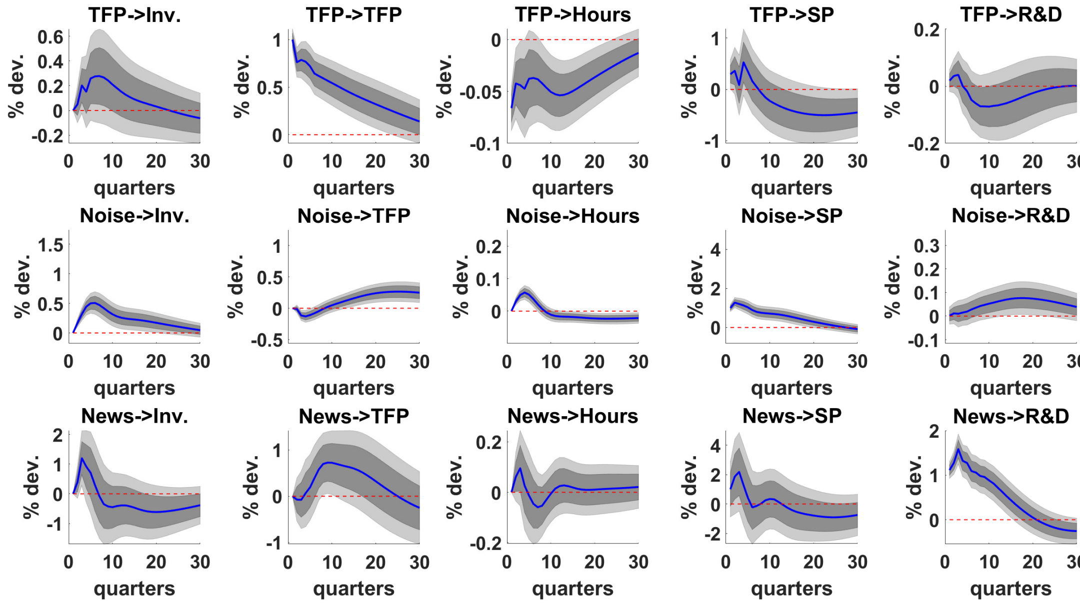
Table 5.5: Skewness, kurtosis and Jarque-Bera-test results for the specification including investment

Reduced form errors	u_1	u_2	u_3	u_4	u_5
Skewness	0.2130	0.2895	0.1210	-1.0434	-0.3712
Kurtosis	3.7496	3.6253	4.6458	6.5580	4.1832
JB-Test p-Value	0.0664	0.0696	0.0037	0.0010	0.0089
Structural shocks	ε_1	ε_2	ε_3	ε_4	ε_5
Skewness	0.2130	0.2911	0.2457	-0.7145	-0.3703
Kurtosis	3.7496	3.9726	3.9146	5.3110	3.9165
JB-Test p-Value	0.0664	0.0223	0.0320	0.0010	0.0191

non-Gaussian at standard significance levels. The Jarque-Bera-test for the structural errors shows that normality can be rejected at the 1% level for ε_4 and at least at the 5% level for ε_5. Consequently, the requirements for the feasibility of the data-driven identification scheme for the non-recursive block seem to be fulfilled.

Figure 5.6 shows the resulting impulse responses of the specification including real private investment. The labeling of news and noise shocks is analogous to before, so ε_4 is interpreted as the noise shock, while ε_5 is labeled as the news shock. As it turns out, the inclusion of investment does not fundamentally change the results from before, a news shock still leads to a significant positive and persistent increase in TFP, stock prices and R&D spending, while the effect of the noise shock is comparably weak. As evidenced by Beaudry and Portier (2006), Barsky and Sims (2011) or Barsky et al. (2015), news shocks lead to business cycle comovement also in investment, as investment increases together with hours and TFP. A noise shock

Figure 5.6: Robustness check including real private investment as an additional control variable. Impulse responses are normalized to an impact effect of one on the main diagonal for the recursive variables and to an impact effect of one on stock prices for both news and noise shocks. Confidence bands are 68% (darker shade) and 90% (lighter shade) bootstrap confidence bands resulting from 5000 resamplings.



also leads to an increase in investment in the short run, but again the effect is much weaker than after a news shock.

To sum up, the present paper's identification approach is able to identify a news shock with standard properties found in the related literature: News shocks lead to business cycle comovement in investment, hours and TFP, while stock prices and R&D expenditures increase in anticipation of higher future productivity in the economy. In the case of noise, the short-run effects go into the same direction as after a news shock: Hours, investment, stock prices and R&D spending increase. However, as there is no direct effect of a noise shock on TFP, but only one through expectations, the medium-run effects on the aforementioned variables are weaker compared to the true news shock. The R&D spending being much more cautious after a noise shock compared to a news shock is robust throughout all specifications, thus there is strong evidence for the crucial assumption to avoid singularity, namely that research spending contains at least partial information about the truth of the news.

5.5 Conclusion

The present paper tries to simultaneously identify news and noise shocks in an SVAR. To solve the singularity issue hailing from a signal extraction problem that is acknowledged in the related literature, it is argued that research spending contains at least partial information about the truth of the news. News is hereby interpreted as information about how much research spending today increases future productivity. As intermediate firms, who are closer to the research and technology adoption process, might have a better insight about the truth of the news compared to other economic agents, their research spending reacts differently to news and noise shocks, providing the missing variation that enables the econometrician to solve the singularity problem. To check the testable implications from the theoretical deliberations, a recently developed identification approach depending on moments beyond the variance is employed that allows to identify news and noise shocks without imposing theoretical restricitions, but by using moment conditions from non-Gaussian structural shocks. The main insight is that both, stock prices and research spending, are forward looking and contain information about news and noise. Consequently, news and noise shocks should lead to a short-run increase in stock prices and research spending, while the news shock should have a stronger effect on the aforementioned variables and TFP compared to a noise shock, because it is the only one that has a direct effect on TFP. In particular, this approach is able to test the assumption of researchers having some information concerning the truth of the news, as the response of research spending should then be weaker after a noise shock compared to a news shock that induces a stock price boom of the same size.

It turns out that the proposed estimation procedure yields a news shock that induces standard business cycle comovement and has a longer-run impact on TFP, stock prices and R&D. The resulting noise shock also yields short-run business cycle comovement, but in contrast to the news shock, the effect on TFP, stock prices and R&D is comparably weak. Furthermore, the data supports the assumption of researchers having partial information about the truth of the news, as under a noise shock that induces the same stock price reaction as the news shock, the research spending response is much weaker. Another interesting observation not recognized by the related literature, which usually does not include an endogenous part of TFP, is that a noise shock leads to a significant increase in TFP in the short run. As noise shocks have no inherent impact on productivity, this effect has to come from the endogenous part of TFP rather than from the exogenous. Firms expect the new ideas to be more productive than usual and invest more into them, thus even though in reality the ideas are not more productive than usual on the balanced growth path, firms overinvest and a short-lived increase in TFP results. Consequently, taking TFP as entirely exogenous, as usually done in the literature regarding news and noise shocks, hides an important transmission channel between news/noise and technological progress: Endogenous innovation decisions largely depend on expectations about the future and thus expected higher productivity leads to more productivity investment today.

5.6 Appendix: How the singularity problem concerning news and noise is solved by an additional signal

This section is intended to show, why including research spending as an additional information source about news and noise shocks solves the singularity problem laid out in Blanchard et al. (2013). As a first step, their argument for a singularity problem is repeated and then the important difference in this paper that solves the problem is explained. In particular, Blanchard et al. (2013) show that there have to be at least as many linearly independent observables for the economic agents as there are structural shocks to be identified. Furthermore, the econometrician cannot generate additional information that are not accessible to the economic agents to solve the singularity problem. The important contribution of the present paper is to argue that research spending provides the necessary additional information concerning news and noise shocks, thus its inclusion in the SVAR solves the singularity problem.

Blanchard et al. (2013) assume a simple illustrative model where productivity a_t has a transitory component z_t and a permanent component x_t and

$$a_t = x_t + z_t. \tag{5.26}$$

The transitory component follows a standard autoregressive law of motion

$$z_t = \rho^z z_{t-1} + \eta_t, \quad \rho^z \in (0, 1) \tag{5.27}$$

and the permanent component follows a unit root process of the form

$$\Delta x_t = \rho^x \Delta x_{t-1} + \varepsilon_t, \quad \rho^x \in (0, 1), \tag{5.28}$$

where Δ denotes first differences. However, households do not directly observe the permanent component x_t, but only a noisy signal s_t and

$$s_t = x_t + \nu_t \tag{5.29}$$

holds. The variables η_t, ε_t and ν_t are i.i.d. shocks, where η_t is interpreted as a transitory TFP shock, ε_t a news shock and ν_t a noise shock. Furthermore, Blanchard et al. (2013) assume that the logarithm of consumption c_t equals the household's long-run productivity expectations

$$c_t = \lim_{j \to \infty} E_t(a_{t+j}) \tag{5.30}$$

and that there is a simple aggregate resource constraint, where output y_t equals consumption

$$y_t = c_t. \tag{5.31}$$

As Blanchard et al. (2013) argue, an SVAR in this case is not able to simultaneously identify all three structural shocks. Observing consumption, productivity and the signal does not suffice to identify three structural shocks, as consumption here is given as a function of productivity and the signal, so does not provide any additional information that can be used to recover the structural shocks. The econometrician is left with two independent reduced form errors but 3 structural shocks, so the SVAR is subject to a singularity problem.

In a next step, Blanchard et al. (2013) show that singularity commonly arises in models with a signal extraction problem: Assume a linear or linearized model and let $\mathbf{y}_t$ be the vector of endogenous state variables, $\mathbf{s}_t$ the m-dimensional vector of observables for representative agents and $\mathbf{x}_{t|t}$ the vector of agents' expectations. Assume there exists a unique stable solution, then the vector of endogenous states can be expressed as a linear function of the information set of the economic agents, which consists of the past realization of $\mathbf{y}_{t-1}$, the observables $\mathbf{s}_t$ and the agents' expectations $\mathbf{x}_{t|t}$

$$\mathbf{y}_t = P\mathbf{y}_{t-1} + Q\mathbf{s}_t + R\mathbf{x}_{t|t}, \tag{5.32}$$

where P, Q and R are matrices containing the undetermined coefficients of the solution. Furthermore, the observables for the econometrician $\mathbf{s^E}_t$ are a linear combination of endogenous states $\mathbf{y}_t$ and agent observables $\mathbf{s}_t$

$$\mathbf{s^E}_t = T[\mathbf{y}_t \quad \mathbf{s}_t], \tag{5.33}$$

where T is a matrix that translates $\mathbf{y}_t$ and $\mathbf{s}_t$ into the econometrician's observables. Solving (5.32) backwards and inserting into (5.33), the econometrician's observables can be formulated in terms of the distributed lags of the agents' observables and expectations

$$\mathbf{s^E}_t = \Xi(L)[\mathbf{s}_t \quad \mathbf{x}_{t|t}]', \tag{5.34}$$

with $\Xi(L)$ the matrices containing the distributed lag parameters (L here refers to the lag operator). The vector of reduced form errors $\mathbf{u}_t$ in a VAR are therefore given by

$$\mathbf{u}_t = \mathbf{s^E}_t - E(\mathbf{s^E}_t | \mathbf{s^E}_{t-1}, \mathbf{s^E}_{t-2}, ...). \tag{5.35}$$

Let the n-dimensional vector of structural errors be $\mathbf{v}_t$. If $n > m$, so the number of shocks is greater than the number of observed variables by the economic agents, the VAR suffers from a singularity problem. Expectations of the agents $\mathbf{x}_{t|t}$ can be expressed as depending on current and past values of the agents' observables $\mathbf{s}_t$ by employing the Kalman filter, so by (5.34) and (5.35) also the econometrician's observables $\mathbf{s^E}_t$ and the reduced form errors $\mathbf{u}_t$ can be expressed depending on current and past values of $\mathbf{s}_t$, thus it follows for the conditional variances

$$Var(\mathbf{v}_t | \mathbf{u}_t, \mathbf{u}_{t-1}, ...) \geq Var(\mathbf{v}_t | \mathbf{s}_t, \mathbf{s}_{t-1}, ...). \tag{5.36}$$

Analogous to (5.35), the residual between the agents' actual and expected observations is given by distributed lags of the structural shocks

$$\mathbf{s}_t - E(\mathbf{s}_t | \mathbf{s}_{t-1}, \mathbf{s}_{t-2}, ...) = \Psi(L)\mathbf{v}_t. \tag{5.37}$$

In consequence, $\Psi(L)$ has to be invertible to recover the structural shocks from the agents' observations. However, as $\Psi(L)$ is $m \times n$ and $m < n$, $\Psi(L)$ is not invertible and thus

$$Var(\mathbf{v}_t | \mathbf{s}_t, \mathbf{s}_{t-1}, ...) > 0 \tag{5.38}$$

and from (5.36) it necessary follows that

$$Var(\mathbf{v}_t | \mathbf{u}_t, \mathbf{u}_{t-1}, ...) > 0, \tag{5.39}$$

so the structural shocks cannot be recovered from the information set of the econometrician, if they cannot be recovered from the information set of the economic agents.

So the singularity problem laid out by Blanchard et al. (2013) comes from the fact that news and noise shocks turn up together in one signal and affect all the other variables only through this one signal. In consequence, the number of structural shocks is by construction greater than the number of observations by the agents. To solve the singularity issue and make SVARs a feasible instrument to simultaneously investigate news and noise shocks, one has to find an additional, linearly independent observable of the agents that contains information about the news and noise shocks. In that case $m = n$ holds and $\Psi(L)$ is invertible. Concerning the simple model example of Blanchard et al. (2013), think of a second signal

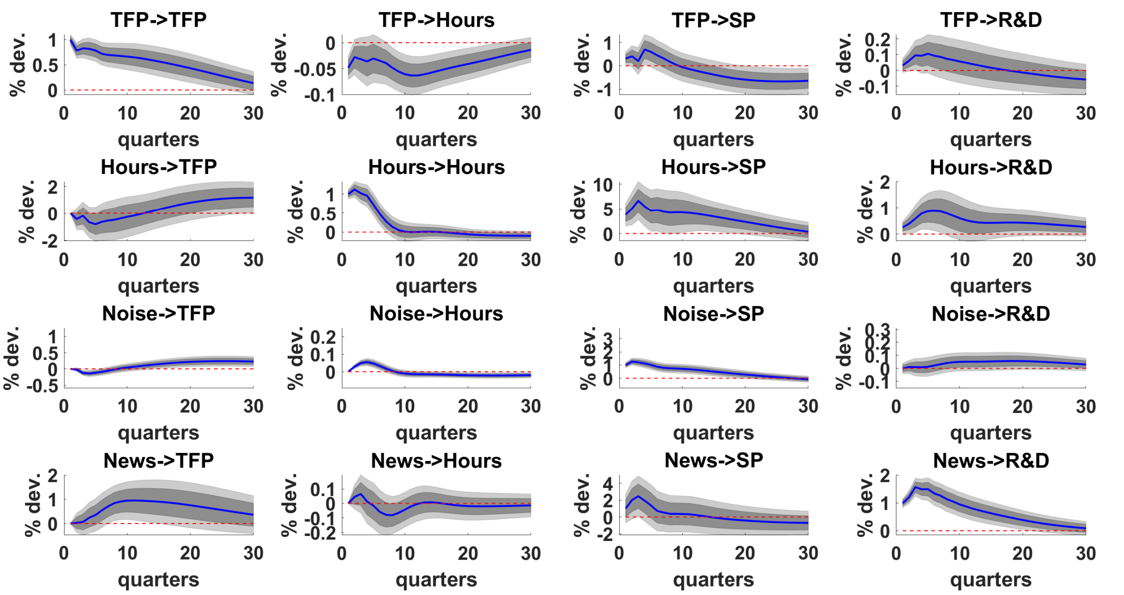
$$s_t^2 = \phi \nu_t, \quad \phi \in (0, 1] \tag{5.40}$$

that at least partly reveals the noise component. The system of equations (5.26), (5.29) and (5.40) is then a system of three linearly independent observables (productivity and the two signals) and three structural shocks (TFP, news and noise shock). Intuitively, the economic agents have one more linearly independent observation and, thus, also the econometrician has the necessary variation available that allows to clearly tell apart news shocks from noise shocks. Consequently, the singularity problem is solved and SVARs are a valid instrument for the analysis. In the main paper research spending and stock prices are argued to be the two independent signals that allow to simultaneously identify news and noise shocks. Research spending is a second signal that analogously to equation (5.40) provides additional information about the veracity of the news that can be exploited in the estimation.

5.7 Appendix: Full set of IRFs for the partly-recursive specification

For completeness, figure 5.7 shows the full set of impulse responses (so also the shock to hours) for the partly-recursive specification. The shock to hours leads to a short-run decrease in TFP, as firms replace quality of labor with quantity. As it becomes easier to employ labor, the expected future value of the firm increases, which can be seen by the immediate and persistent increase in stock prices. As it becomes more attractive to stay in the market, competition in innovation increases and R&D expenditures increase immediately. The increase in innovation then leads to an increase in TFP in the medium run after about 20 quarters. The finding of shocks to the labor market having longer-run effects on technological progress is consistent with the findings of Mortensen (2005), Wheeler (2007) or Martellini and

Figure 5.7: Full set of IRFs from the partly-recursive specification (so additionally including the hours shock). Impulse responses are normalized to an impact effect of one on the main diagonal for the recursive variables and to an impact effect of one on stock prices for both news and noise shocks. Confidence bands are 68% (darker shade) and 90% (lighter shade) bootstrap confidence bands resulting from 5000 resamplings.



Menzio (2020), as well as the second chapter of this dissertation.

5.8 Appendix: Further robustness checks

5.8.1 Changing the number of lags

In the main body of the paper, the lag order was chosen ad hoc as traditional information criteria are based on a normality assumption for the structural shocks and thus collide with the identifying assumption of at least some non-Gaussian structural shocks. However, changing the number of lags can sometimes have a serious impact on the distributional properties of the estimated shocks. In order to check on the sensitivity of the results in the main paper, a smaller and larger lag order is tried out in this section. At first consider a specification with 3 lags included, as indicated by the Akaike information criterion. Sticking to the AIC, table 5.6 shows the skewness, kurtosis and Jarque-Bera test results under the smaller lag order. As it can be seen, there is still evidence that three of the four reduced form errors are

Table 5.6: Skewness, kurtosis and Jarque-Bera-test results for the specification with 3 lags as implied by the AIC

Reduced form errors	u_1	u_2	u_3	u_4
Skewness	0.2595	-0.1156	-1.3157	-0.2650
Kurtosis	3.5463	4.7978	8.3599	4.1139
JB-Test p-Value	0.1097	0.0023	0.0010	0.0155
Structural shocks	ε_1	ε_2	ε_3	ε_4
Skewness	0.2595	-0.1965	-1.1086	-0.2496
Kurtosis	3.5463	4.8255	7.5171	3.8022
JB-Test p-Value	0.1097	0.0020	0.0010	0.0457

non-Gaussian, indicating that there has to be at least one non-Gaussian structural shock. Looking at the Jarque-Bera test for the structural shocks, normality can be rejected at the 1% level for ε_3 and at the 5% level for ε_4, thus there is still evidence for the feasibility of the identification approach relying on moments beyond the variance.

Figure 5.8 shows the resulting impulse responses for the specification containing only 3 lags. The basic properties of the results in the main paper remain unchanged: A news shock leads to a persistent increase in stock prices, R&D and TFP, while the effect of a noise shock on the previous variables is weaker in comparison. The crucial findings of the present paper remain untouched and are robust to the reduction of lags compared to the partly-recursive specification.

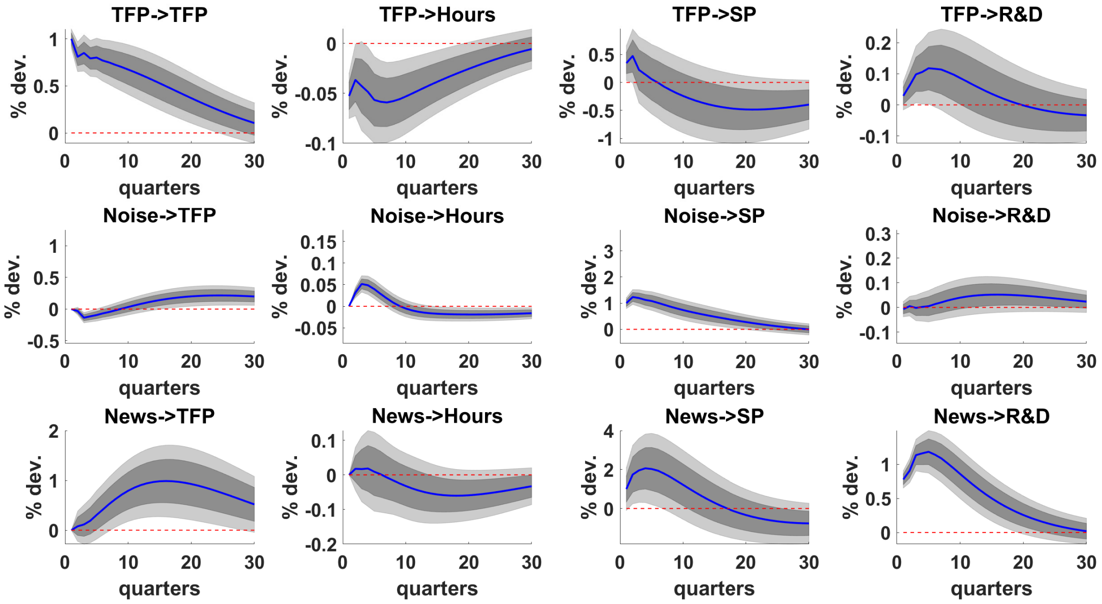
On the other side, the number of four lags used in the main paper might be too low to capture all the important dynamics, so as a further robustness check a larger lag order of six is chosen. Table 5.7 shows the respective skewness, kurtosis and Jarque-Bera test results. Again three of the reduced form errors are significantly

Table 5.7: Skewness, kurtosis and JarqueBera-test results for the specification with 6 lags

Reduced form errors	u_1	u_2	u_3	u_4
Skewness	0.2646	-0.0492	-0.9582	-0.3232
Kurtosis	3.0760	4.3367	6.3117	3.6101
JB-Test p-Value	0.3335	0.0111	0.0010	0.0599
Structural shocks	ε_1	ε_2	ε_3	ε_4
Skewness	0.2646	-0.0933	-0.8065	-0.2020
Kurtosis	3.0760	3.9645	5.5889	3.4004
JB-Test p-Value	0.3335	0.0407	0.0010	0.2883

non-Gaussian at usual significance levels. Looking at the Jarque-Bera test results

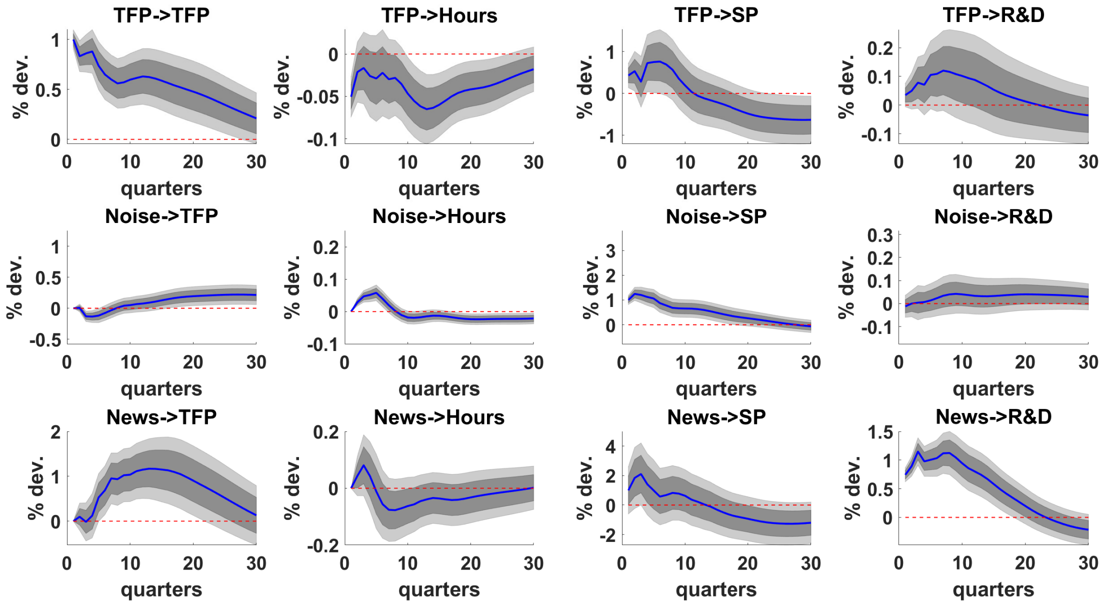
Figure 5.8: Robustness check with 3 lags as implied by the Akaike information criterion instead of 4 lags. Impulse responses are normalized to an impact effect of one on the main diagonal for the recursive variables and to an impact effect of one on stock prices for both news and noise shocks. Confidence bands are 68% (darker shade) and 90% (lighter shade) bootstrap confidence bands resulting from 5000 resamplings.



for the identified structural shocks, it shows that normality can be rejected for ε_3 at the 1% level. Consequently, there is evidence that the requirements for the data-driven identification scheme are fulfilled.

Figure 5.9 shows the resulting impulse responses. It turns out that the main implications of the paper are robust to adding more lags to the specification: The news shock leads to an immediate and persistent increase in stock prices and real R&D expenditures, while TFP increases with a small lag and stays at a higher value than without the shock in the medium run. On the other hand, a noise shock also leads to an increase in TFP, stock prices and R&D spending, but the shock effect on TFP is weaker than compared to after a news shock. Furthermore, news and noise shocks both lead to an increase in hours, thus the business cycle comovement property is robust to the change in specification as well. While the qualitative results remain unchanged, the inclusion of more lags increases the width of the confidence bands, making the response of research spending to a noise shock entirely insignificant, the same holds for the stock price reaction to a news shock. So the inclusion of more lags decreases precision without changing the qualitative results, thus the smaller

Figure 5.9: Robustness check with 6 lags instead of 4 lags. Impulse responses are normalized to an impact effect of one on the main diagonal for the recursive variables and to an impact effect of one on stock prices for both news and noise shocks. Confidence bands are 68% (darker shade) and 90% (lighter shade) bootstrap confidence bands resulting from 5000 resamplings.

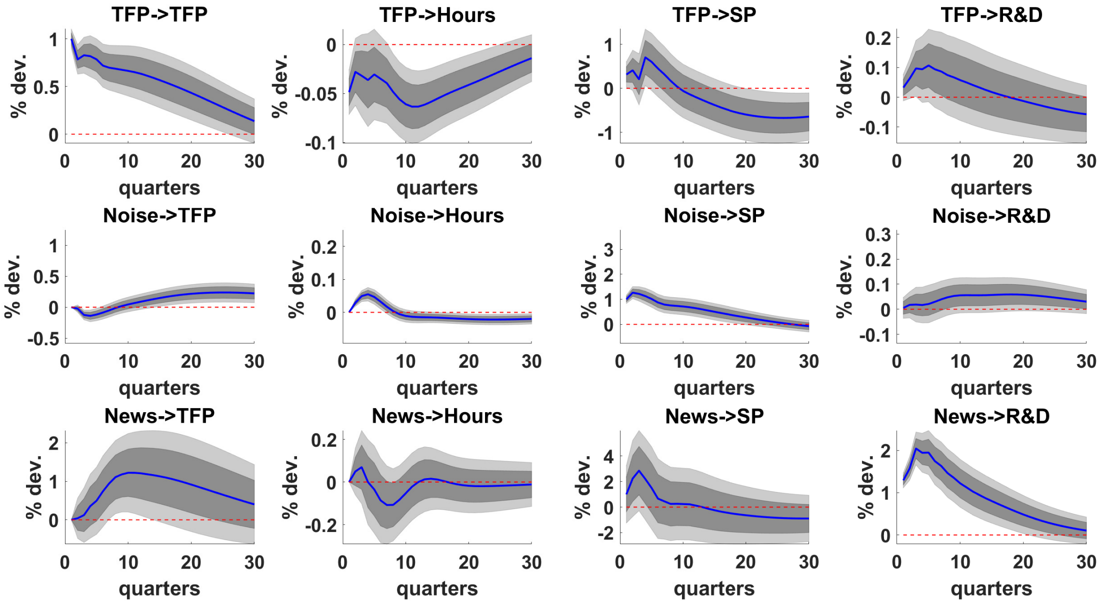


lag order is preferred in the main body of the paper. Summing up, the results from the paper are robust to alternating the lag order.

5.8.2 Using a different estimator for the non-recursive block

The estimator following Keweloh (2019) used in the main section of the present paper is a GMM estimator using the higher shock moments as moment conditions. A different way to estimate the non-recursive block is using a pseudo maximum likelihood (PML) approach (see Gouriéroux et al. (2017)). To see if the estimator used before and/or its computational implementation are driving the results from the main body of the paper, the PML estimator is used instead for the non-recursive block as a robustness check. The labeling assumptions are analogous to before. Figure 5.10 shows the resulting impulse responses. As it can be seen, the results from the main part of the paper are robust to the change of the estimator. A news shock still leads to an immediate and persistent increase in stock prices and R&D spending and with a short lag to a persistent increase in TFP. Analogously, the noise shock induces an increase in stock prices, R&D spending and TFP as well,

Figure 5.10: Robustness check using the PML estimator following Gouriéroux et al. (2017) for the non-recursive block. Impulse responses are normalized to an impact effect of one on the main diagonal for the recursive variables and to an impact effect of one on stock prices for both news and noise shocks. Confidence bands are 68% (darker shade) and 90% (lighter shade) bootstrap confidence bands resulting from 5000 resamplings.



but the effect is comparably weak. Furthermore, for a noise shock that induces the same stock price reaction as a news shock, the reaction in research spending is much weaker, hinting that researchers are likely to have additional information about the veracity of the news. Both shocks robustly lead to business cycle comovement in hours. Consequently, the results found in the main part of the paper are not sensitive to the choice of the estimator.

6 Concluding remarks

The present dissertation complements the recent stream of literature that tries to integrate short-run business cycle fluctuations and long-run technological progress. It therefore adds endogenous technological progress to otherwise standard real business cycle (RBC) models and takes a look on the longer-run implications of classical business cycle shocks like matching efficiency, inflation target, monetary policy, news and noise shocks.

After the introductory first chapter, the second chapter analyses, how matching efficiency shocks affect the firm's innovation decision. It is noted that the slowdown in TFP growth during the Great Recession was accompanied by an outward shift in the Beveridge Curve, which is typically thought to be induced by a strong decline in matching efficiency during this time. It is argued that this outward shift in the Beveridge Curve was a major contributor to the slowdown in endogenous TFP growth. Lower matching efficiency implies higher hiring costs for firms, thus a higher entry barrier for potential market entrants. As in Schumpeterian growth models the competition for higher productivity due to new ideas between incumbent firms and entrants is vital for technological progress, higher entry costs reduce the incentive to innovate for all firms and thus long-run technological progress. The empirical assessment of the model shows that, even though quite irrelevant during other times, the decline in matching efficiency was the driving force behind the slowdown in endogenous TFP growth during the Great Recession, even before demand and TFP shocks.

The third chapter deals with the observation that, even though higher inflation is linked with lower long-run growth, expansive monetary policy is typically found to be beneficial for technological progress. It is argued that longer-run deviations of the inflation rate are associated with inflation target shocks rather than monetary policy shocks, who are assumed to be only short-lived. Thus decisions about the longer-run technological progress are not concerned by traditional monetary policy shocks, but only by inflation target shocks. If the inflation target is increased, the economy experiences a period of adjustment to the new long-run inflation rate. In a Newkeynesian model, price markups decrease during this period and thus the gain of being market incumbent. As argued before, in Schumpeterian models technological progress depends on the incentive of firms to engage in innovative competition, thus if this incentive is reduced, technological progress will be reduced. The empirical assessment of the model shows that expansive monetary policy has the commonly observed feature of increasing TFP growth, while longer-run changes in the inflation target due to inflation target shocks reduce technological progress.

The fourth chapter takes a look at monetary policy and stock market shocks from a more econometric point of view. Both, monetary policy and stock markets, are likely to instantaneously react to shocks originating from the respective other agent, which makes short-run restrictions not viable for identifying SVARs containing the nominal interest rate and stock returns. The previous chapter already discussed the matter of monetary policy affecting long-run technological progress, thus even a long-run restriction might be problematic. A partly recursive, partly data-driven identification scheme to solve this identification problem is proposed and monetary policy shocks are found to have an instantaneous and long-run negative effect on stock prices and output, supporting the results from the previous chapter.

The fifth chapter examines the effect of true news and noise on technological progress in an SVAR. In line with the other chapters, news is interpreted as shocks to the idea production, which can only have a lagged effect on TFP due to necessary technology adoption beforehand. It is assumed that stock prices and research spending contain information regarding news, while researchers have an informational advantage concerning the truth of research related news compared to all other economic agents, which allows to estimate the SVAR without running into a singularity problem. The main result is that true news shocks lead to an immediate increase in research spending and stock prices, which is comparably strong, while noise shocks that induce the same stock price reaction are associated with a much more cautious response in research spending and a weaker effect on TFP and stock prices. The difference in the response of research spending confirms the assumption that researchers might have at least partial information about the truth of research related news.

Summing up, the present dissertation discusses longer-run effects of traditional business cycle shocks that are not recognized so far. Knowing about the long-run implications of short-run events is not only of academic value, but is also important for political decisions or strategic planning of private firms and households. Further research will shed more light on the matter and likely render the classical dichotomy between short- and long-run obsolete.

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