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LONG-RUN MONETARY NON-NEUTRALITY, MENU COSTS AND DEMAND-SUPPLY INTERACTIONS: THE LESSONS OF SOME AGENT-BASED SIMULATIONS

Miklós Váry

Abstract

This paper investigates whether two possible phenomena, the presence of fixed adjustment costs (menu costs) related to firms' price adjustment and demand-supply interactions are able to serve as theoretically and empirically plausible explanations for the empirical evidence supporting the violation of long-run monetary neutrality. An agent-based menu cost model is developed and calibrated to reproduce some important empirical stylized facts about price changes, which are revealed using a micro-level dataset from the U.S. It is shown that it is possible to come up with model variants, in which the presence of menu costs causes monetary shocks to have permanent real effects, but if firms are assumed to be hit by idiosyncratic productivity shocks, long-run monetary neutrality holds even in the presence of menu costs. Idiosyncratic productivity shocks are necessary for the model to produce realistically large price changes. However, the presence of demand-supply interactions, i.e. a positive feedback from the output gap to potential output leads to long-run monetary non-neutrality even in model variants with good empirical fit. In the fully-fledged calibrated model variant, around one quarter of a typical monetary shock is absorbed by real output in the long run. This suggest that monetary policy may have substantial long-run real effects. Two limitations of long-run expansionary monetary policy are pointed out. First, its effectiveness decreases with the size of the monetary shock. Second, if price adjustment is asymmetric because of the presence of trend inflation, there is an intermediate range of the shock size, within which negative monetary shocks are more effective in the long run than positive ones.[1]

Journal of Economic Literature (JEL) codes: E12, E31, E32, E37, E52
Keywords: long-run monetary non-neutrality, menu costs, demand-supply interactions, agent-based model

> *"… the course of events cannot be predicted, either in the long period or in the short, without a knowledge of the behavior of money between the first state and the last. … And it is this which we ought to mean when we speak of a monetary economy … the next task is to work out in some detail a monetary theory of production … the task on which I am now occupying myself, in some confidence that I am not wasting my time."*
>
> John Maynard Keynes, 1933
> Cited by Davidson (1987, p. 146)

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1. INTRODUCTION

Long-run monetary neutrality has been a cornerstone of mainstream monetary macroeconomics since the groundbreaking essays of David Hume, *On Money* and *On Interest*. (Lucas, 1996) Money is neutral in the long run, if a permanent shock to the *level* of money supply (or equivalently, a transitory shock to the *growth rate* of money supply) does not have a permanent effect on the real variables of the economy.[2] (Lucas, 1996; Bullard, 1999) The mainstream approach towards long-run monetary neutrality is represented well by the following statement that Robert Lucas has made in his Nobel Lecture: "… [long-run] *monetary neutrality… … needs to be a central feature of any monetary or macroeconomic theory that claims empirical seriousness*". (Lucas, 1996, p. 666)

The long-run neutrality of money has some important practical implications for the conduct of monetary policy. If money is actually neutral in the long run, then the best that central banks can hope for is to exert some *short-run* stimulating effects on real economic activity. In the long-run, all changes induced by the central bank in nominal aggregate demand will be absorbed by the price level. Although monetary policy may be effective in the short run because of the presence of nominal rigidities, the primary focus of central banks should be to maintain a low and stable inflation rate, and to smooth short-run cyclical fluctuations in order to reduce the welfare losses caused by the presence of imperfect price adjustment, as they are unable to influence real economic activity in the long run. Thus, long-run monetary neutrality is a core preassumption behind the optimality of the policy of strict inflation targeting suggested to central banks by early New Keynesian monetary theories. (Woodford, 2003; Galí, 2008)

In spite of its widespread acceptance, the empirical evidence for long-run monetary neutrality is far from being unambiguous.[3] The first research that applied appropriate non-stationary econometric techniques – a bivariate autoregressive integrated moving average (ARIMA) framework – to test long-run monetary neutrality was conducted by Fisher and Seater (1993). Surprisingly, they were able to *reject* the null hypothesis that permanent shocks to the level of money supply did not affect the level of real output permanently. Thus, they found using annual data that long-run monetary neutrality had not held in the U.S. between 1869 and 1975. Subsequent papers have shown that the finding of long-run monetary non-neutrality fails, if post-war U.S. data are used that do not include the periods of World War II and the Great Depression (Boschen – Otrok, 1994; Boschen – Mills, 1995; King – Watson, 1997), if other countries, e.g. Canada (Haug – Lucas, 1997) or Australia (Olekalns, 1996) are examined, while keeping the periods of World War II and the Great Depression in the sample, or if the money supply is measured by monetary aggregates other than M1 (Weber, 1994; Coe – Nason, 1999).

However, Atesoglu (2001) found using a longer and more recent annual dataset than those applied in the studies cited above that real GDP and the money stock had been cointegrated in the U.S. between 1947 and 1998. The long-run equilibrium relationship

[2] In this paper, I do not deal with the issue of long-run monetary *superneutrality*, i.e. the question whether permanent shocks to the *growth rate* of money supply affect the *level* of real variables in the long run. See Orphanides – Solow (1990) for a comprehensive survey about the theoretical literature of long-run monetary superneutrality.

[3] See Bullard (1999) for an excellent survey about the empirical literature of long-run monetary neutrality and superneutrality.

found using the Johansen (1991) procedure indicates that permanent monetary shocks have permanent real effects, hence money cannot be neutral in the long run. Atesoglu and Emerson (2009) repeated the previous exercise with a larger and even more recent quarterly post-war (1959-2006) sample from the U.S., and extended it to a multivariate setting. They were looking for cointegrating relationships between blocks of nominal and real macroeconomic variables, and found convincing evidence against long-run monetary neutrality. As their sample consists of U.S. data, but it does not include the periods of World War II and the Great Depression, their results invalidate a huge part of the cited criticism aimed against the results of Fisher and Seater (1993). De Grauwe and Costa Storti (2004) argue that the reason why monetary policy has no long-run real effects in many structural vector autoregression (SVAR) studies is that long-run monetary neutrality is often used as an identifying assumption for generating impulse response functions. If different identifying assumptions are applied, then monetary policy usually has long-run real effects.[4] There is another line of literature, which presents clear empirical evidence for the claim that too tight monetary policy during recessions leads to permanent real economic losses. (Ball, 1999; Stockhammer – Sturn, 2012) This finding can also be interpreted as evidence against long-run monetary neutrality.

To sum up, the empirical evidence about long-run monetary neutrality is mixed: it may hold, but its empirical validity is not as obvious as most mainstream macroeconomists believe. If one finds the evidence against long-run monetary neutrality convincing, one has to find an economic mechanism that is able to serve as a plausible explanation for it theoretically, as well as empirically. Theoretical explanations can be found in the post-Keynesian economic literature. Following the thoughts of Keynes cited as the motto of this paper, post-Keynesians have always believed that money is not neutral in the long run. However, according to earlier post-Keynesian interpretations, it is not the quantity, but it is the *existence* of money that is not neutral, meaning that a monetary economy works in a substantially different way compared to a barter economy, in which any good can be chosen to be a numeraire just like in basic models of general equilibrium. (Davidson, 1987) The mainstream interpretation of long-run monetary neutrality or non-neutrality is difficult to be reconciled with the framework of post-Keynesian monetary macroeconomics, since the endogeneity of money belongs to its core assumptions, hence an exogenous shock to the money supply, the arrival of which is assumed in the definition of long-run monetary neutrality, makes no sense. (Cottrell, 1994)

Still, there is a more recent line of post-Keynesian research that can be related to mine. This argues that the long-run Phillips curve is not vertical, hence there is a long-run trade-off between inflation and real economic activity. This implies that if an exogenous money supply is assumed – in contrast to the post-Keynesian view about endogenous money –, then the *quantity* of money will not be neutral in the long run, either. Post-Keynesian authors name two possible reasons for the emergence of the long-run trade-off. (Fontana, 2007; Fontana – Palacio-Vera, 2007; Kriesler – Lavoie, 2007)

[4] It has to be noted that De Grauwe and Costa Storti (2004) measure the long-run real effect by the 5-year impulse response of real GDP to a 1 percentage point increase in the nominal interest rate, which is obviously an imperfect measure of the long-run real effect, since long-run monetary neutrality requires real output to return to its initial value on an *infinite* horizon after the monetary shock has hit, and not on a 5-year horizon.

1. *Nonlinear price adjustment*: Within an intermediate range of the rate of capacity utilization (or the output gap), prices do not adjust to exogenous shocks, therefore the short-run, as well as the long-run Phillips curve is horizontal. The typical explanation for this horizontal segment in the Phillips curve is that decreasing returns do not prevail in the vicinity of the normal rate of capacity utilization (or the potential output), hence positive demand shocks lead to price increases, only if capacity utilization is high enough for decreasing returns to show up in production. An equivalent assumption not emphasized by the papers cited above is that firms have to face fixed costs, when they change their prices. (Barro, 1972; Sheshinski – Weiss, 1977; Akerlof – Yellen, 1985; Blanchard – Kiyotaki, 1987) These fixed costs of price adjustment are often labeled as "menu costs" (Mankiw, 1985), and they lead to the emergence of an inaction band around the normal rate of capacity utilization, within which firms will not adjust their prices in response to demand shocks, as it is not worth paying the menu cost in exchange for a slight increase in profits. Just like the lack of decreasing returns in the vicinity of the normal rate of capacity utilization, menu costs imply that firms will only react to large enough demands shocks by changing their prices. In the rest of the paper, I am going to apply the menu cost interpretation of nonlinear price adjustment, since it is better known from the context of menu cost models often used for analyzing the extent of *short-run* monetary non-neutrality.
2. *Demand-supply interactions*: Potential output or equivalently, the natural rate of unemployment is path-dependent: actual output/unemployment affects potential output or the natural rate. The positive feedback from actual towards potential real activity can manifest itself through three possible channels: the labor force, the capital stock and technological progress. In the labor market, large negative demand shocks may increase long-term unemployment, the loss of skills of the long-term unemployed reduces their employability, thereby the potential labor force. (Phelps, 1972; Cross, 1987) An insider-outsider mechanism of wage bargaining, during which the employed bargain for the highest expected real wage that allows them to stay employed, may also hinder the return of the long-term unemployed to the labor market. (Blanchard – Summers, 1986, 1987; Galí, 2015) Concerning the capital stock, if firms have to face some sunk adjustment costs related to market entry (Baldwin – Krugman, 1989; Dixit, 1989, 1992), or to the initiation of their investment activity (Bassi – Lang, 2016), then the capital stock may not return to its initial value, as the demand shock dies away, leading to lower potential output. The interdependence between profits and investments may also lead to a permanently smaller capital stock during recessions, when firms' profitability is low. This may slow down technological progress, as well, since innovations are often manifested in the form of capital goods. (Arestis – Sawyer, 2009) Technological progress may slow down as a result of a feedback from short-run economic growth to the growth rate of productivity, as well. This feedback is known as the Kaldor-Verdoorn law. (Kaldor, 1957; Verdoorn, 1949; Setterfield, 2002; Dutt, 2006; Storm – Naastepad, 2012) The law tries to capture the weakening of learning by doing and the reduced profit incentives of firms to engage into research and development

during recessions.[5] The effects work in the opposite direction for positive demand shocks.[6] Note that the above-mentioned economic mechanisms are often summarized as *demand-led growth*, or *hysteresis* in the literature. (Fontana, 2007; Fontana – Palacio-Vera, 2007; Kriesler – Lavoie, 2007) Following Arestis and Sawyer (2009), I prefer using the term *demand-supply interactions*, as hysteresis refers to a general property of a dynamic system, meaning that transitory shocks exert a permanent effect on its steady state. (Amable et al., 1993; Cross, 1993; Göcke, 2002) The possible economic mechanisms behind hysteresis include demand-supply interactions, but other types of economic mechanisms – e.g. fixed cost of price adjustment, as it will become clear in *Section 4* – are also able to result in hysteretic macrodynamics. (Setterfield, 2009)

Based on the results of the literature summarized above, my research tries to find the answers for the following three broad questions:

1. *Do the presence of menu costs and demand-supply interactions actually lead to long-run monetary non-neutrality within the framework of a quantitative monetary model?* Concerning demand-supply interactions, the answer is probably yes, as mathematical models can already be found in the post-Keynesian literature, in which a positive feedback from actual output (unemployment) to potential output (to the natural rate of unemployment) results in long-run real effects of monetary policy. (Lavoie, 2006; Setterfield, 2009) The answer is less clear in the case of menu costs. Dixit (1991) and Delgado (1991) present menu cost models with a perfectly rational, dynamically optimizing representative firm, in which the presence of menu costs leads to hysteresis in the price level and in real output. In these two papers, hysteresis means that transitory nominal shocks have permanent effects on the mentioned variables. But if the effects of transitory nominal shocks are permanent, it seems reasonable to suspect that the effects of *permanent* nominal shocks would turn out to be permanent, as well, resulting in long-run monetary non-neutrality. However, in recent dynamic stochastic general equilibrium (DSGE) models of menu cost economies, which have been developed to study the *short-run* real effects of monetary policy, money is neutral in the long-run. (Golosov – Lucas, 2007; Gertler – Leahy, 2008; Nakamura – Steinsson, 2010; Midrigan, 2011; Alvarez et al., 2016; Karádi – Reiff, 2019) This is puzzling in light of the results of Dixit (1991) and Delgado (1991). I try to find out what the conditions are for menu costs to lead to long-run monetary non-neutrality, and what the conditions are for them to result in long-run monetary neutrality.
2. *Which sets of conditions can be considered more plausible empirically: those, under which menu costs and/or demand-supply interactions lead to long-run monetary non-neutrality, or those, under which they do not?* My aim with answering this question is to find out whether long-run monetary non-neutrality is just an interesting theoretical possibility in menu cost models, or a phenomenon with important practical relevance for monetary policy. In order to answer this question,

[5] See Arestis – Sawyer (2009) for an exhaustive discussion about the role of demand-supply interactions in generating path-dependent macrodynamics.

[6] However, it has to be noted that the empirical evidence for the effects of positive demand shocks on the natural rate of unemployment is weaker than that for the effects of negative demand shocks. (Ball, 2009)

I calibrate all of my model variants to match the most important moments of two empirical distributions related to product-level price changes. The empirical distributions stem from one of the most popular empirical samples containing micro-level price changes, the Dominick's dataset, which is often used for calibrating menu cost models. (Midrigan, 2011; Alvarez et al., 2016) I assess the empirical plausibility of each model variant by analyzing how well it is able to capture key moments of the empirical distributions.

3. *What is the extent of long-run monetary non-neutrality in reality?* After answering the first two questions under some simplified sets of conditions, I present a fully-fledged model variant, which is able to capture all the important empirical moments of the empirical distributions related to price changes. This gives me the opportunity to come up with a rough empirical estimate for the extent of long-run monetary non-neutrality. The importance of such an estimate is outstanding for monetary authorities, as it equips them with information about how strong their long-run influence is on real economic activity.

To find answers for my questions, I build up an agent-based menu cost model with boundedly rational firms, which allows me to study the behavior and the interactions of many heterogeneous agents instead of assuming the existence of a representative one. (Leijonhufvud, 2006; Tesfatsion, 2006) Agent-based models are becoming increasingly popular tools in macroeconomic research. (Dosi et al., 2010, 2015; Delli Gatti et al., 2005, 2011; Dawid et al., 2012; Assenza et al., 2015; Gaffeo et al., 2015; Fagiolo – Roventini, 2017; Guerini et al., 2018) Babutsidze (2012) presents an example for an agent-based menu cost model. Setterfield and Gouri Suresh (2016) argue that agent-based models are especially useful for studying demand-supply interactions, and more generally, path-dependent macrodynamics, since many path-dependent phenomena are *emergent phenomena*: they cannot be observed at the micro level of the economy, but they "emerge" at the macro level as a result of interactions between heterogeneous microeconomic agents. Agent-based models have been developed for the analysis of such emergent phenomena. (Tesfatsion, 2006)

First, I use the model to show that the presence of menu costs does lead to long-run monetary non-neutrality in its simplest variants, because if firms do not adjust their prices perfectly in the short run, then long-run price adjustment to a monetary shock cannot be perfect, either, provided that firms are not hit by any other type of shock. Then, I turn to examining why menu costs do not lead to long-run monetary non-neutrality in standard DSGE-type menu cost models. I identify two crucial differences between the simplest variants of my agent-based menu cost model and DSGE-type menu cost models, which may be responsible for their different implications regarding long-run monetary neutrality. On the one hand, I assume in the spirit of agent-based computational economics that firms are boundedly rational, while DSGE-type menu cost models contain perfectly rational, dynamically optimizing firms. Forward-looking firms might conclude that it is rational to pay the menu cost in the short-run in order to avoid infinite long-run losses caused by the lack of perfect price adjustment. I build up a simple variant of my model with dynamically optimizing firms, and I find that long-run monetary non-neutrality holds in that model variant, as well. The reason for this is that forward-looking firms discount the stream of their expected future profits: the present value of the expected losses caused by the lack of perfect price adjustment is finite, hence it may turn out to be smaller than the cost of price adjustment.

On the other hand, it is assumed in DSGE-type menu cost models that firms are hit by idiosyncratic productivity shocks. I show that once idiosyncratic productivity shocks are introduced to the simplest variants of my model, money becomes neutral in the long run. The reason for this is that all firms are expected to be hit by an idiosyncratic shock sooner or later while the monetary shock dies away, and it forces them to adjust their prices to the monetary shock, as well. In the long run, this results in perfect price adjustment. Thus, idiosyncratic productivity shocks are the reason why money is neutral in the long run in DSGE-type menu cost models. Since idiosyncratic productivity shocks are necessary to reproduce the large mean size of empirical price changes (Golosov – Lucas, 2007), I conclude that it is possible to build theoretical models, in which menu costs lead to long-run monetary non-neutrality, but they are not plausible empirically.

Then, I show that demand-supply interactions do result in long-run monetary non-neutrality, even if firms are assumed to be hit by idiosyncratic productivity shocks. The explanation is that potential output changes during the short-run quantitative adjustment to the monetary shock, hence real aggregate output adjusts to an altered potential level in the long run. I come up with a fully-fledged variant of my model, which is able to fit all the important moments of the empirical distributions related to price changes, and produces long-run monetary non-neutrality in the presence of demand-supply interactions. Under my calibration, it predicts that 23.08% (around one quarter) of a typical monetary shock is absorbed by real aggregate output in the long run, while the remaining 76.92% (around three quarters) of the shock is passed through to the price level. This suggests that monetary policy may have substantial long-run real effects in reality.

However, this does not mean that central banks can stimulate the real economy in the long run without any limitations. I show that the long-run pass-through of a monetary shock to real output decreases with the size of the monetary shock, hence the effectiveness of long-run expansionary monetary policy worsens, and its inflationary effects are amplified, as the monetary stimulus becomes larger and larger. The reason for this is that larger monetary shocks lead to a larger increase in the fraction of firms that adjust their prices in the short run in response to the shock, but if short-run real effects are smaller, then demand-supply interactions will lead to a smaller increase in potential output, as well. I also show that the long-run real effects of positive and negative monetary shocks are asymmetric in the presence of trend inflation. For an intermediate range of the shock size, negative monetary shocks are more effective than positive ones, since the effect of negative shocks on the fraction of price adjuster firms is weaker. The reason for this is that firms recognize after the arrival of a negative monetary shock that trend inflation will reduce the relative prices of their products soon, even if they do not pay the menu cost. However, for small shock sizes, for which the fraction of price adjuster firms is not affected substantially, positive monetary shocks have slightly larger long-run real effects than negative ones. The same is true for very large shock sizes, for which almost all firms adjust their prices in the short run in response to the shock. In these two cases, the key factor determining the extent of the long-run real effect is the strength of price adjustment for the adjusting firms. Empirically, price decreases are rarer, but larger than price increases. This stronger downward price adjustment is reflected in the calibration of my model, hence the long-run real effects of positive monetary shocks turn out to be larger than those of negative ones in the two extreme ranges of the shock size. Still, for large, but not impossibly large sizes of the shock, negative monetary shocks are more effective than positive ones, implying that it might be easier for central banks to hurt the real economy in the long run, than to stimulate it.

My results have crucial implications for the conduct of monetary policy. They serve as another argument against the policy of strict inflation targeting. But they also imply that central banks should put even more emphasis on following real targets – besides following their primary target of maintaining a low and stable inflation rate –, than according to those, who have argued for short-run output stabilization so far. If money is actually not neutral in the long run, then short-run disinflations cause long-run damages to the real economy that might not be compensated by the benefits of disinflation. Fontana and Palacio-Vera (2007) suggest that central banks should design their monetary policies following a "flexible opportunistic" approach: they should not react to small inflationary shocks, thereby they can avoid causing a reduction in potential output. Instead, they should wait for another exogenous shock to take inflation back to its target rate. However, in case of deflationary shocks, nominal aggregate demand should be increased, even if the shock is small, as this action might lead to long-run real benefits.

The rest of the paper is organized as follows. In *Section 2*, I present the micro-level dataset used to derive the empirical distributions related to price changes, as well as the key properties of the distributions which should be reproduced by my model. I present my agent-based menu cost model and its calibration in *Section 3*. In *Section 4*, I examine the conditions, under which menu costs do or do not lead to long-run monetary non-neutrality in some simple variants of my model. I turn to analyzing the role of demand-supply interactions in generating long-run monetary non-neutrality in *Section 5*, I use my fully-fledged model variant to come up with a rough estimate for the long-run real effects of monetary shocks, and I discuss the two above-mentioned limitations of long-run expansionary monetary policy. Finally, I conclude the most important findings of my research in *Section 6*.

2. THE EMPIRICAL DATA

Before I start presenting my agent-based menu cost model, it is important to summarize the stylized empirical facts that the model is required to reproduce. I will assess the empirical plausibility of the different variants of my model by analyzing how well they are able to fit to the key moments of two empirical distributions concerning product-level price changes: the distribution of nonzero price changes and the distribution of the frequencies of price changes.

I derive these two empirical distributions using a micro-level dataset, which is often applied for calibrating menu cost models, the Dominick's dataset. (Midrigan, 2011; Alvarez et al., 2016) It consist of scanner price data collected by the James M. Kilts Center for Marketing of the University of Chicago Booth School of Business. The dataset contains 9 years (1989-1997) of weekly store-level data about the prices of more than 9000 products collected in 86 stores of the Dominick's Finer Foods retail chain in the Chicago area. As prices are highly correlated across stores, Midrigan (2011) has decided to work with the prices of one single store, which has the largest number of observations. He has made the resulting dataset available in the Supplemental Material to his paper: this is the dataset that I work with. The data were collected during a time period, when there was no substantial economic turmoil in the United States. Thus, if my model is calibrated on their basis, it will provide a picture about the long-run real effects of monetary shocks during normal times.

My model does not contain any incentives for firms to engage into temporary sales, therefore I sales-filter the data to obtain time series about regular prices. I use the algorithm developed by Kehoe and Midrigan (2008) to filter out temporary sales.[7] I time-aggregate the resulting weekly time series of regular prices to a monthly frequency by keeping every fourth observation of the time series only. The monthly frequency of the resulting sample is closer to the quarterly frequency of GDP data that I will use for estimating some parameters of my model. This leaves me with a sample consisting of 100 months long time series of regular prices for 9450 different products. For the sake of precaution, I follow Midrigan (2011), and keep only those price observations, for which the calculated regular price is equal to the observed price. As the number of missing values is large in the dataset, I am left with 391763 available price observations. Finally, I compute all nonzero regular price changes as the log-difference of subsequent monthly prices, and I drop all regular price changes with a size greater than the 99th percentile of the size distribution of price changes in order to get rid of outliers. The final sample consists of 22630 observations of nonzero monthly regular price changes.

Midrigan (2011) reports the mean frequency of price changes, but he does not derive their whole empirical distribution. I derive it, as I will need some of its further moments for calibrating some parameters of my model. I start with calculating the frequency of monthly regular price changes for each of the 9450 products. I do this by dividing the number of months, in which the price of the product has changed with the total number of months, for which the price observation, as well as the observation of the previous month are non-missing. Then, I drop all products, for which the calculated frequency is equal to 0. I do this, because it seems unlikely that the price of a product does not change at all for 9 years, hence missing values are the most probable reason for not registering any price changes for these products. Keeping these products in the sample would lead to a downward bias in the mean of the frequency distribution of price changes. Finally, I drop all products with a frequency of price change greater than the 99th percentile of the frequency distribution in order to get rid of outliers.[8] The final sample consists of the frequencies of regular price changes for 7765 products.

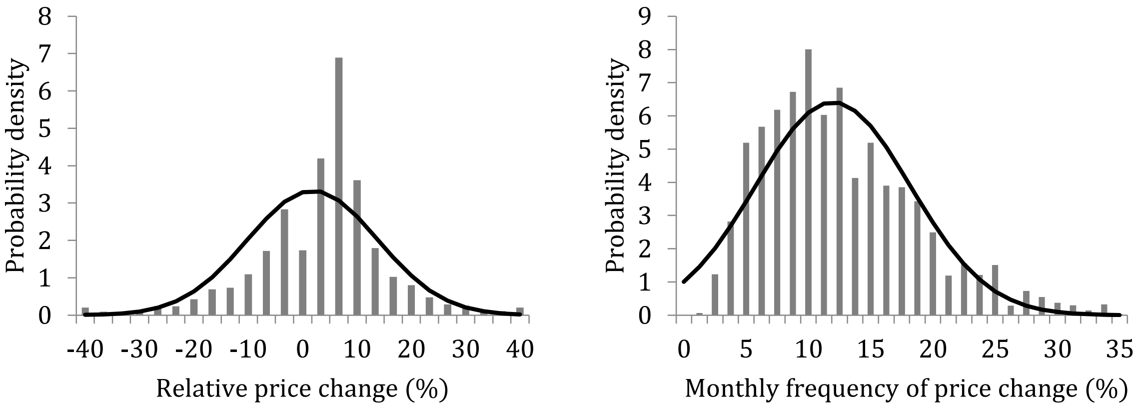
Figure 1 presents the two empirical distributions. Superimposed are the probability density functions of the normal distribution with equal means and variances. Graphical inspection of *Figure 1* supplemented with the calculation of some key moments of the two distributions reveals some important stylized facts about price changes that I require my model to reproduce. All the calculated moments are weighted: I weigh all price changes and all frequencies of price changes related to a certain product with the share of that

[7] The Matlab codes for the sales-filtering algorithm, as well as for calculating the moments of the empirical distribution of nonzero price changes are available in the Supplemental Material to Midrigan (2011). Appendix 1 of the same Supplemental Material describes the sales-filtering algorithm in detail.

[8] As the number of observations available to calculate the frequencies of price changes are different for each product, I weigh the price change frequency of every product with the number of observations available to calculate it while computing the percentiles of the frequency distribution.

product in the basket of the average customer of Dominick's. This is possible, because the Dominick's dataset does not only contain data about the transaction prices faced by the consumers, but about the quantities sold to them, as well. In case of the distribution of the frequencies of price changes, I use another weight in addition to the consumption shares for calculating its moments: I weigh the frequencies of price changes of different products with the number of observations available to calculate them, as it is different for each product because of the numerous missing values present in the dataset.

Figure 1: The Empirical Distributions of Nonzero Price Changes (left panel) and the Frequencies of Price Changes (right panel)



Note: Both histograms are based on the data available in the Supplemental Material to Midrigan (2011).

The most important stylized facts and the empirical values of the key moments are the following:

1. *The mean size of price changes is large* (9.7%). My model obviously needs to reproduce this fact for the strength of price adjustment to be realistic.
2. Still, *many price changes are small*. To be specific, 28.9% of all price changes are smaller than half of the mean size of price changes.
3. The simultaneous presence of many small price changes and some very large price changes implies that *the distribution of nonzero price changes exhibits substantial excess kurtosis* compared to the normal distribution (4.28 versus 3.00). Alvarez et al. (2016) prove that it is crucially important for all menu cost models to reproduce the kurtosis of the empirical price change distribution, since it sufficiently summarizes information about the strength of the so called *selection effect*, i.e. the effect that price adjuster firms are not randomly selected, as in the Calvo (1983) model of sticky price adjustment, but firms with larger differences between the actual and the desired prices of their products are more likely to respond to an exogenous shock with a price change. The strength of the selection effect plays an important role in determining the extent of short-run real effects of monetary shocks in menu cost models. (Caplin – Spulber, 1987; Golosov – Lucas, 2007; Midrigan, 2011) It seems reasonable to suspect that it strongly influences the extent of long-run real effects, as well, if there are any.
4. *The standard deviation of price changes is large* (12.5%). I will use this moment to pin down the standard deviation of idiosyncratic productivity shocks in my model.

5. *The mean nonzero price change is* 1.9%. This moment will be useful for producing a realistic amount of trend inflation in my model.
6. *Price increases are more frequent than price decreases*. Specifically, 66.0% of all price changes are price increases.
7. Nevertheless, if prices are decreased, then *the mean size of price decreases* (11.0%) *is larger than that of price increases* (9.0%). The mean size of price increases is 81.8% of the mean size of price decreases. The two latter stylized facts are important to be reproduced, if one would like to analyze whether the long-run real effects of positive and negative monetary shocks are asymmetric or not.
8. *Price changes are rare* for the average product. The mean monthly frequency of price changes is 11.6%. This moment is obviously important to be reproduced by the model in order to generate a realistic degree of price stickiness. According to Alvarez et al. (2016), it is the other key moment besides the kurtosis of the price change distribution that determines the extent of short-run real effects of monetary shocks in menu cost models, hence it will probably be important for the long-run real effects, as well.
9. *The distribution of the frequencies of price changes is skewed to the right*: the prices of most products change in around 5-15% of the months, but there are some products with frequencies of price changes above 30%. The skewness of the distribution is equal to 0.62. This information will help me generate a realistic degree of heterogeneity in the frequencies of price changes, which will play an important role in one of my simple model variants.

The above-mentioned stylized facts can be considered as standard: they have all been reported before in the empirical literature of sticky price adjustment. (Bils – Klenow, 2004; Klenow – Kryvtsov, 2008; Nakamura – Steinsson, 2008) They are confirmed even by those studies that are based on microdata collected by the U.S. Bureau of Labor Statistics (BLS) for calculating the Consumer Price Index. BLS data cover a wider range of product categories than scanner price data collected in supermarkets like Dominick's, but scanner price data have the advantage of containing a much larger number of observations than BLS data. Müller and Ray (2007) and Chen et al. (2008) present detailed empirical evidence for the two stylized facts concerning asymmetric price adjustment (6 and 7) using the Dominick's dataset.[9]

3. THE AGENT-BASED MENU COST MODEL

In this section, I present my agent-based menu cost model and its calibration. I model the goods market of an economy, the supply side of which consists of N monopolistically competitive firms, each of them selling G different types of goods. The assumption of multiproduct firms is often applied in menu cost models to generate a sufficiently large amount of small price changes. (Midrigan, 2011; Alvarez et al., 2016; Karádi – Reiff, 2019) All product varieties sold in the goods market are differentiated from each other.

[9] These micro-level asymmetries in price adjustment are supported by many different empirical studies based on various datasets from various countries. Babutsidze (2012) summarizes the results of these empirical studies.

3.1. The Demand Side of the Market

I assume that the demand side of the market consists of a perfectly rational representative household that behaves according to the Dixit-Stiglitz model of monopolistic competition. (Dixit – Stiglitz, 1977) The assumption of a perfectly rational representative household is rather unusual in an agent-based economic model, but it substantially simplifies the technical details of the model without altering its core message, and it facilitates comparison with standard DSGE-type menu cost models. In menu cost models, the important nominal and real adjustments take place in the supply side of the market, therefore the demand side is usually modeled as simply as possible.

The household decides about the demanded quantities of the different product varieties in a way that maximizes its utility subject to its budget constraint. Mathematically, it solves the following conditional optimization problem in each period:

$$\max_{c_{i,g,t}} C_t(c_{1,t}, c_{2,t}, \dots, c_{N,t}) = \left(\sum_{i=1}^{N} c_{i,t}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}$$

$$\text{s.t.} \quad c_{i,t} = \left(\sum_{g=1}^{G} c_{i,g,t}^{\frac{\gamma-1}{\gamma}}\right)^{\frac{\gamma}{\gamma-1}}$$

$$\sum_{i=1}^{N}\sum_{g=1}^{G} p_{i,g,t}c_{i,g,t} = Y_t,$$

where c stands for the consumed quantities and p stands for the prices. The i subscript refers to the firms, the g subscript denotes the different product varieties supplied by the same firm, and the t subscript stands for the time periods, which will be taken to a month during the calibration. C denotes the utility of the household, which will be used to measure aggregate consumption in the model. The utility function is assumed to be of a CES type (CES – *Constant Elasticity of Substitution*), where $\varepsilon > 1$ is the absolute value of the across-firm elasticity of substitution. The first constraint of the problem expresses $c_{i,t}$ as a CES aggregate of consumed quantities of the goods supplied by firm i, where $\gamma > 1$ is the absolute value of the across-good elasticity of substitution. The second constraint of the problem is the household's budget constraint, where Y denotes nominal aggregate demand, or equivalently, the nominal income of the representative household. The budget constraint expresses that total spending on the different product varieties has to be equal to the household's nominal income.

By solving the household's utility-maximization problem, one can derive its demand functions for the $N \times G$ product varieties. The household's demand function for variety g supplied by firm i is given by

$$c_{i,g,t} = \left(\frac{p_{i,g,t}}{p_{i,t}}\right)^{-\gamma}\left(\frac{p_{i,t}}{P_t}\right)^{-\varepsilon}\frac{Y_t}{P_t}, \tag{1}$$

where the price level in period t is given by the CES price index $P_t = \left(\sum_{i=1}^{N} p_{i,t}^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}$, and the firm-level price index is $p_{i,t} = \left(\sum_{g=1}^{G} p_{i,g,t}^{1-\gamma}\right)^{\frac{1}{1-\gamma}}$. These definitions of the price indices assure that the measured price level will express the price of one unit of utility provided that the household spends its income in an optimal way, and they imply that nominal aggregate expenditure is equal to P_tC_t. The interpretation of demand function (1) is rather intuitive: the demanded quantity of a given product variety decreases ceteris paribus, if it becomes more expensive compared to the other varieties supplied by the same firm, and the household wants to buy less from a firm, if its price index increases relative to the market price level. The last factor expresses that a rise in the household's real income increases the demanded quantities of all product varieties, assuming that their relative prices remain unchanged.

There is only one question left to answer: how is the household's nominal income determined? This is where monetary policy comes into the picture: I assume that the central bank is able to control nominal aggregate demand perfectly according to an exogenous stochastic process.[10] Let g_t^Y denote the gross growth rate of nominal aggregate demand in period t, i.e. $g_t^Y = Y_t/Y_{t-1}$. I assume that nominal aggregate demand is growth-stationary, i.e. its growth rate follows a first order autoregressive (AR(1)) process:[11]

$$\log g_t^Y = (1-\varphi)\log \bar{g}^Y + \varphi \log g_{t-1}^Y + \xi_t, \tag{2}$$

where $\bar{g}^Y$ is the gross trend growth rate of nominal aggregate demand, and $\varphi \in [0,1)$ determines the persistence of nominal demand growth. Finally, $\xi_t \sim N(0,\sigma_\xi^2)$ is an independent, identically normally distributed random variable with mean 0 and variance σ_ξ^2. ξ_t represents the value of the monetary shock in period t.

Y_t could also be labeled as the nominal money supply, if one assumed that the total money stock gets directly into the hands of the representative household. I think that the label "nominal aggregate demand" fits to the concept of the model better. Nakamura and Steinsson (2010) use the same term for Y_t.[12]

3.2. The Supply Side of the Market

At this point, I depart from the assumptions of the Dixit-Stiglitz model, and turn on the agent-based nature of my model. The supply side of the market is populated by N heterogeneous, monopolistically competitive firms: they are the agents in the model. I assume that each firm has a so called *supply potential* $\bar{q}_{i,g,t}$ for all of its supplied product varieties, which changes in time. The supply potential can be interpreted as the optimal scale of production, the amount of output corresponding to the optimal plant size, the produced quantity corresponding to the normal level of capacity utilization, or as some

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[10] My assumption that the central bank controls the household's nominal income directly is a shortcut for the usual practice followed in DSGE-type menu cost models, according to which the functional form of the utility function is chosen in a way, which assures that nominal income will be proportional to nominal money supply in case of optimal behavior. See Golosov – Lucas (2007) for the necessary restrictions on the utility function.

[11] The same AR(1) process is assumed for nominal money growth in the menu cost models of Midrigan (2011) and Karádi and Reiff (2019). In case of the former, the constant term is missing, since trend inflation is assumed away.

[12] Nakamura and Steinsson (2010) state that the assumption, according to which the central bank is able to control nominal aggregate demand through equation (2) can be justified by a model of demand, in which nominal aggregate demand is proportional to nominal money supply, and the central bank follows a money growth rule.

kind of a micro-level potential output.[13] Firms try to set their prices in a way that equalizes the demand for their products with their supply potentials. If at least one of their products is produced in a quantity different from its supply potential, then they suffer losses compared to the maximal attainable amount of profits. It must be possible to formulate an optimization problem for firms, the solution of which would determine $\bar{q}_{i,g,t}$ as a function of input prices and some technological parameters. However, for the purposes of this study, it is sufficient to assume that the supply potentials are state variables for all firms: their values are determined before firms make their price decisions.

The price decision of firms consists of two steps: first, they decide whether to change the prices of their products or not. Second, if they have decided to change them, they have to determine the new prices. I assume in line with the views of Simon (1972), with the perspective of post-Keynesian economics (Lavoie, 2014), with the spirit of agent-based computational economics (Tesfatsion, 2006; Dosi, 2012; Fagiolo – Roventini, 2017) and with the experimental evidence of behavioral economics (Tversky – Kahneman, 1974; Camerer et al., 2004) that firms are boundedly rational. They do not have a perfect knowledge about the data-generating process underlying the economic environment, in which they operate because of the cognitive limitations of their decision-makers, and because the complexity of the economic environment makes it impossible to gather all the relevant information necessary for optimal decision-making. Specifically, firms do not know equations (1) and (2): the demand functions for their products and the stochastic process determining the evolution of nominal aggregate demand. Therefore, they are not able to make optimal decisions, they seek for satisfying ones instead. I think about boundedly rational decision-making the same way as Simon (1972): because of their inability to make optimal decisions, firms use heuristics, i.e. simple "rules of thumb" for making their decisions. Heuristics make it possible for firms to easily arrive at decisions that are in accordance with their profit-maximizing motivations by simplifying the decision problem. (Gigerenzer, 2008; Hommes, 2013) In this sense, the decisions made are satisfying, but not optimal.

Using the terminology of post-Keynesian economics, this is equivalent to assuming that firms face fundamental uncertainty instead of risk, when they make their choices regarding the future: they do not know the probability distributions of the relevant random variables influencing their decisions. (Knight, 1921; Keynes, 1921) In my model, the reasons for the presence of fundamental uncertainty can be described by the human abilities/characteristics approach, according to which the probability distributions could be known in principle, but the agents are not able to discover them because of their limited cognitive abilities, or because of the lack of necessary information. (O'Donnell, 2013) In such a situation, the rational thing to do is to use simple adaptive behavioral rules, i.e. heuristics, which allow firms to adapt to the fundamentally uncertain economic environment through a learning process characterized by trial and error. (Gigerenzer, 2008)

In my model, firms use a heuristic rule for making their price decisions.[14] The rule is in accordance with firms' motivation to produce close to the supply potentials of their products, as it helps coordinating demand with them. The presence of menu costs implies

[13] I have borrowed the term „supply potential" from Arestis and Sawyer (2009).

[14] According to survey data from the U.K., 65% of the surveyed firms set their prices primarily using rules of thumb, or on the basis of past or current information. Only 35% of the surveyed firms claim that they set their prices in a forward-looking way. (Greenslade – Parker, 2012)

that it is not worth changing the prices, if the anticipated demanded quantities of the firm's products are close to their supply potentials, since the loss implied by the menu cost would probably offset the potential gains of the price changes. In line with DSGE-type menu cost models with multiproduct firms, I assume that firms enjoy economies of scope when changing the prices of their products: if they pay the menu cost, they can reprice all of their products, even those that are only slightly mispriced.[15] This assumption helps generating a realistic amount of small price changes in the model. (Midrigan, 2011; Alvarez et al., 2016; Karádi – Reiff, 2019)

Specifically, firms pay attention to the anticipated value of an index, which measures the average extent of disequilibrium in the submarkets of their supplied product varieties. I assume that the production of the product varieties is demand-determined, thus produced quantities $q_{i,g,t}$ are equal to demanded quantities: $q_{i,g,t} = c_{i,g,t}$ for $\forall i, g, t$. Before making their price decisions, firms form expectations about the excess demand $\hat{q}_{i,g,t}$ for each of their supplied products by computing the percentage deviation between their anticipated demand-determined output and their supply potential:

$$\hat{q}^{e}_{i,g,t} = \frac{q^{e}_{i,g,t} - \bar{q}_{i,g,t}}{\bar{q}_{i,g,t}},$$

where x^e denotes the firm's expectation for the value of any variable x.

The anticipated value of the "disequilibrium index" for firm i in period t is denoted by $\hat{q}^{e}_{i,t}$, and is calculated as

$$\hat{q}^{e}_{i,t} = \sqrt{\frac{\sum_{g=1}^{G}\left\{\left[1 - \theta \cdot I\left(\hat{q}^{e}_{i,g,t} < 0\right)\right] \cdot \hat{q}^{e}_{i,g,t}\right\}^2}{G}},$$

where $\theta \in [0, 1]$ is a measure of the asymmetry of price adjustment, and $I(\,)$ is the indicator function, which returns 1, if anticipated product-level excess demand is negative, otherwise it returns 0. If θ was equal to 0, then $\hat{q}^{e}_{i,t}$ would simply measure the average anticipated extent of disequilibrium in the submarkets of the product varieties supplied by firm i in period t. But I assume that $\theta > 0$, thus firms assign a lower weight to those of their products, for which they expect excess supply, when they form their expectations about the value of the firm-level disequilibrium index. The reason for this is that although firms do not know the specific form of stochastic process (2) governing nominal aggregate demand, I assume that they are able to observe the inflation rate, hence they are aware of the fact that there is trend inflation in the economy ($\bar{g}^{Y} > 1$). In the presence of trend inflation, the relative price of a product is decreasing, even if its nominal price is unchanged. Under such circumstances, it seems reasonable that the anticipated excess supply required by a firm to decrease the price of a concerned product is larger than the anticipated excess demand required to increase it. This way, the firm is able to save on the menu cost by letting trend inflation move the relative prices of its products with anticipated excess supply in the desired direction.[16]

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[15] Midrigan (2011) presents empirical evidence for economies of scope in price setting across different goods sold by Dominick's.

[16] Assuming a perfectly rational single-product firm, Ball and Mankiw (1994) show that the gap required between the actual and the desired price to induce a price change is larger in the case of price decreases than in the case of price increases, if there is trend inflation in the economy. I generalize their idea to a multi-

The presence of menu costs leads to the emergence of an inaction band around zero anticipated firm-level disequilibrium, within which firms keep their prices unchanged. Let z_i denote the price adjustment threshold of firm i, i.e. the anticipated value of the disequilibrium index, above which the firm changes the prices of its products. This threshold value is assumed to be heterogeneous across firms. The value of z_i is not determined by the menu cost alone: it may also depend e.g. on the time preferences of the firm's decision-makers, or on their perception about the uncertainty of the economic environment. Nevertheless, the price adjustment threshold would not exist, if firms faced no menu costs associated with their price changes, and it is reasonable to assume that the threshold depends positively on the amount of menu costs to be paid.[17]

The heuristic price decision rule can be written as:

$$p_{i,g,t} = \begin{cases} p_{i,g,t-1}\left(\frac{q^e_{i,g,t}}{\bar{q}_{i,g,t}}\right)^{\alpha^U}, \text{ if } \hat{q}^e_{i,t} > z_i \text{ and } \hat{q}^e_{i,g,t} > 0 \\ p_{i,g,t-1}\left(\frac{q^e_{i,g,t}}{\bar{q}_{i,g,t}}\right)^{\alpha^D}, \text{ if } \hat{q}^e_{i,t} > z_i \text{ and } \hat{q}^e_{i,g,t} < 0 \\ p_{i,g,t-1}, \qquad \text{if } \hat{q}^e_{i,t} \le z_i \end{cases}, \tag{3}$$

where $\alpha^U \in [0, 1]$ is a parameter determining the strength of *upward* price adjustment, and $\alpha^D \in [0, 1]$ is another parameter determining the strength of *downward* price adjustment. According to price decision rule (3), firms keep their prices unchanged if the anticipated value of their disequilibrium index does not exceed their price adjustment threshold. However, if it exceeds the price adjustment threshold, firms will adjust their prices based on anticipated excess demand. If firm i expects demand for its good g to be greater than its supply potential, then it will raise its price in order to decrease demanded quantity. In the opposite case, the firm will lower the price with the intention to increase demanded quantity, bringing it closer to the supply potential. The sizes of the price changes are regulated by parameters α^U and α^D. As price decreases are empirically larger than price increases according to stylized fact 7 reported in *Section 2*, I expect the value of α^U to turn out to be smaller than α^D during the calibration of the model. According to U.K. survey data collected by Greenslade and Parker (2012), such a result could be explained by firms' fear that their consumers will not tolerate large price increases. Large price decreases are better justified, as they may help stealing consumers from the competitors.

Note that firms rely solely on information that are available for them locally, when they make their price decisions: they do not need any global information about the state of the goods market.[18] This is in line with the views of Hayek (1945), the theory of autonomous control (Kornai – Martos, 1973) and the lessons of agent-based computational economics (Leijonhufvud, 2006; Gaffeo et al., 2015; Guerini et al., 2018), according to which

product setting. The other important difference between their perspective and mine is that I do not assume that the asymmetry of price adjustment measured by θ is optimally chosen.

[17] As I have mentioned in the *Introduction*, the lack of decreasing returns near the supply potential is an alternative explanation for the presence of a price adjustment threshold in a single-product setting. However, it would be difficult to explain why a multiproduct firm without decreasing returns near the supply potentials of its products and without the necessity to pay menu costs changes the prices of its products always at the same time.

[18] Except of the knowledge about the presence of trend inflation.

individual decisions based solely on local information together with the local interactions of agents are able to keep the economic system around a relatively stable global state.[19]

After firms have made their price decisions, the household decides about the quantities demanded and produced for all product varieties.

There are three details to be clarified concerning price decision rule (3):

1. What is the distribution of price adjustment thresholds across firms?
2. How do firms form their expectations about demand?
3. What determines the evolution of supply potentials?

The individual price adjustment thresholds are drawn from a lognormal distribution, which is an asymmetric probability distribution, hence it allows the model to reproduce stylized fact 9, according to which the frequency distribution of price changes is skewed to the right, as well as stylized fact 8, according to which the mean frequency of price changes is low. Specifically, I assume that

$$\log z_i \sim N\left(\log\left(\frac{\bar{z}^2}{\sqrt{\bar{z}^2+\sigma_z^2}}\right), \log\left(\frac{\bar{z}^2+\sigma_z^2}{\bar{z}^2}\right)\right),$$

where $\bar{z} > 0$ and $\sigma_z > 0$ are parameters. The above parameterization of the normal distribution assures that the mean price adjustment threshold is exactly equal to $\bar{z}$ and the standard deviation of price adjustment thresholds equals σ_z.

I assume that firms use a very simple adaptive rule to form their expectations about the demand for their products. They expect that the demanded quantities in the current period will be equal to the quantities demanded in the previous period:[20]

$$q_{i,g,t}^e = q_{i,g,t-1}.$$

The evolution of supply potentials is determined by two stochastic processes. I assume that the supply potential of good g produced by firm i in period t can be decomposed into two components as

$$\bar{q}_{i,g,t} = \mu_t \cdot \delta_{i,g,t},$$

where μ_t is the aggregate component of the supply potential, which is common to all product varieties supplied in the market, and $\delta_{i,g,t}$ is the good-specific component of the supply potential, which is independent across firms, but is correlated across the goods produced by the same firm, as well as in time.

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[19] The assumed price decision rule conditional on adjustment is inspired by Kornai and Martos (1973), who assume that firms decide about their production on the basis of the difference between the actual and the desired amount of their inventories. Duménil and Lévy (1991) assume the same decision rule as Kornai and Martos (1973), but for prices instead of produced quantities. Since there are no inventories in my model, I substitute the deviation of the actual level of inventories from its desires one with that of the actual value of anticipated output from its desired one. In agent-based economic models, it is also standard to assume that prices or markups react to excess demand either directly (Leijonhufvud, 2006; Guerini et al., 2018), or indirectly through the deviation of the actual amount of inventories from the desired one (Lengnick, 2013; Gaffeo et al., 2015).

[20] Gigerenzer and Brighton (2009) argue that the simplest heuristics are more successful in fundamentally uncertain environments than more sophisticated ones. Dosi et al. (2017) examine this idea within the context of an agent-based macroeconomic model, and find that the simple adaptive rule that I assume for forming demand expectations beats the forecasting performance of more sophisticated rules, like least squares learning.

Let $g_t^{\mu} = \mu_t/\mu_{t-1}$ denote the gross growth rate of the aggregate component. I assume that its evolution is determined by the following stochastic process:

$$\log g_t^{\mu} = \log \bar{g}^{\mu} + \eta(\log Q_{t-1} - \log \bar{Q}_{t-1}) + \nu_t, \tag{4}$$

where $\bar{g}^{\mu} > 0$ is the gross potential growth rate of the economy in steady state, $Q_t = \left(\sum_{i=1}^{N} q_{i,t}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}$ is the real aggregate output of the economy computed as the CES aggregate of firm-level aggregate outputs, and $\bar{Q}_t = \left(\sum_{i=1}^{N} \bar{q}_{i,t}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}$ is the potential output of the economy calculated as the CES aggregate of the potential outputs of firms. Firm-level aggregate output $q_{i,t} = \left(\sum_{g=1}^{G} q_{i,g,t}^{\frac{\gamma-1}{\gamma}}\right)^{\frac{\gamma}{\gamma-1}}$ is the CES aggregate of the quantities of the product varieties supplied by the firm, and the potential output of a firm $\bar{q}_{i,t} = \left(\sum_{g=1}^{G} \bar{q}_{i,g,t}^{\frac{\gamma-1}{\gamma}}\right)^{\frac{\gamma}{\gamma-1}}$ is the CES aggregate of the supply potentials of the products supplied by the firm. $\eta \in [0, 1]$ is a parameter determining the strength of demand-supply interactions, and finally, $\nu_t \sim N(0, \sigma_\nu^2)$ is an independent, identically normally distributed random variable with mean 0 and variance σ_ν^2. It represents the aggregate productivity shock in the model.

Equation (4) can be interpreted as follows. If the actual output of the economy equals its potential output, and it is not hit by an aggregate productivity shock, then the aggregate component of the supply potentials grows at the rate of $\bar{g}^{\mu} - 1$. If the output gap of the economy is positive ($Q_t > \bar{Q}_t$), then the potential growth rate rises above its steady state value. If the output gap is negative ($Q_t < \bar{Q}_t$), then the potential growth rate falls below its steady state value. The strength of this interaction between the demand-determined actual output and the supply-determined potential output is regulated by parameter η. The possible economic explanations for the presence of these demand-supply interactions are detailed in the *Introduction*. I assume that demand-supply interactions take place between *aggregate* actual and potential output at the macro level of the economy, and not at the micro level. On the one hand, this will allow me to estimate η using macroeconomic data instead of micro-level data. On the other hand, it seems reasonable to assume that a recessionary macroeconomic environment worsens the growth prospects for *all* firms, not just for those that are forced to produce below the supply potentials of their products. As I have mentioned in the *Introduction*, long-term unemployment increases during recessions, the quality and the quantity of the active labor force deteriorates, which is an aggregate effect, reducing the opportunities of all firms to hire workers with sufficiently strong skills. Aggregate productivity growth slows down during recessions, making it more difficult for all firms to benefit from knowledge spillovers, etc. Of course, the presence of an aggregate productivity shock may overwrite the effects of the first two terms on potential growth in equation (4).[21]

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[21] Equation (4) is inspired by Lavoie (2006), who has come up with a similar equation, according to which the change in the natural rate of unemployment depends positively on the difference between the actual and the natural rate. Equation (4) contains real output instead of unemployment, and it is amended with potential growth, as well as an aggregate productivity shock.

The evolution of the good-specific component of the supply potential is determined by the following stochastic process:

$$\log \delta_{i,g,t} = \rho \log \delta_{i,g,t-1} + \zeta_{i,g,t},$$

where $\zeta_{i,g,t}$ is a random variable, which represents an idiosyncratic productivity shock that hits the supply potential of good g supplied by firm i in period t, and $\rho \in [0,1)$ is a parameter determining the persistence of idiosyncratic productivity shocks.

An appropriate assumption about the distribution of idiosyncratic productivity shocks allows the model to reproduce the shape of the empirical distribution of nonzero price changes, which crucially influences the real effects of monetary shocks. Following Gertler and Leahy (2008) and Midrigan (2011), I assume that the distribution of idiosyncratic productivity shocks is leptokurtic. This way, the model will be able to reproduce the substantial excess kurtosis of the empirical distribution of nonzero price changes. Specifically, I assume that idiosyncratic productivity shocks arrive infrequently, according to a Poisson process:

$$\tilde{\zeta}_{i,g,t} = \begin{cases} 0 & \text{with probability } 1-\lambda \\ N\left(0, \frac{\sigma_\zeta^2}{\left[1+\frac{\chi(2+\chi)}{G}\right]\lambda}\right) & \text{with probability } \lambda\text{'} \end{cases}$$

where $\lambda \in [0,1]$ is the probability of the arrival of a nonzero shock, and $\chi > 0$ is a parameter to be introduced soon, which influences the correlation between productivity shocks hitting the supply potentials of goods produced by the same firm. Conditional on arrival, the shocks are drawn from a normal distribution with mean 0 and variance $\sigma_\zeta^2/\{[1+\chi(2+\chi)/G]\lambda\}$. I prove in *Appendix A* that this parameterization of the normal distribution assures that the variance of idiosyncratic productivity shocks $\zeta_{i,g,t}$ will exactly be equal to σ_ζ^2.

I assume that good-specific productivity shocks are uncorrelated across firms, but are correlated across the goods produced by the same firm. I introduce within-firm correlation between good-specific productivity shocks the same way as Midrigan (2011) has done. The actual realizations of good-specific productivity shocks are determined as

$$\zeta_{i,g,t} = \tilde{\zeta}_{i,g,t} + \chi \text{mean}_g\left(\tilde{\zeta}_{i,g,t}\right). \tag{5}$$

I prove in *Appendix B* that if one would like the within-firm correlation of productivity shocks to be equal to $\rho_\zeta \in [-1,1)$[22], then

$$\chi = \frac{\sqrt{1+\rho_\zeta[(1-\rho_\zeta)G-(2-\rho_\zeta)]}}{1-\rho_\zeta} - 1. \tag{6}$$

This way, the value of ρ_ζ can be set as a parameter, and the value of χ is determined automatically according to equation (6).

[22] I do not allow the within-firm correlation of good-specific productivity shocks to be equal to 1, since the denominator of the ratio in equation (6) would be 0 in that case.

3.3. Simulations

The nonlinearities and the different forms of heterogeneity present in the model do not allow for an analytical solution, therefore I rely on computer simulations for analyzing its behavior. Simulations are started from a situation, in which the market is not hit by either aggregate, or idiosyncratic shocks, the actual quantities produced are equal to the supply potentials, and all variables are constant in time. I set the initial values of supply potentials to $\bar{q}_{i,g,0} = 1$ for $\forall i, g$ and the initial value of nominal aggregate demand to $Y_0 = N \times G$. This implies that nominal demand per product variety is equal to 1, and prices also need to be equal to 1 initially. I let the simulation run for 1000 periods: this amount of simulation time is enough for a steady state joint distribution of relative prices and supply potentials to emerge.[23] Then, I let the simulation run for another T periods, and discard the first 1000 periods of the simulation. This way, I assure that the statistics computed from the simulated time series will not be biased by the initial adjustment towards a steady state.

In case of simulating impulse response functions to monetary shocks, I follow a similar procedure. First, I simulate a $1000 + T$ periods long baseline path for the variables without monetary shocks, but with aggregate and idiosyncratic productivity shocks present. Then, I simulate another path using the same random numbers, but with a monetary shock of a given size arriving in period 1002. I calculate the percentage deviations between the two simulated paths of the variables, discard the first 1000 periods, and treat period 1001 as period 0. I repeat this exercise 10000 times, and average out the 10000 time series for each variable. The resulting time series are going to approximate the conditional expectations for the deviations between the values of the variables on the baseline path and on the path hit by the monetary shock, where there are two conditions:

1. The variables are forecasted from period 0, when the market is in steady state.
2. The central bank generates a monetary shock of a given size in period 1, and sets $\xi_t = 0$ for $\forall t > 1$.

The resulting conditional forecasts are the impulse response functions of the variables of interest.[24] This way, I will be able to assess, whether a particular permanent shock to the level of nominal aggregate demand interacting with the two different types of productivity shocks that are expected to arrive, while the monetary shock dies away, has a permanent effect on the level of real aggregate output in expectation, or not. If it has, then long-run monetary neutrality fails in the model.

During the simulations, the timing of events within a given period is the following:

1. The central bank determines nominal aggregate demand by coming up with a realization for the monetary shock.
2. Firms find out the supply potentials of their products after the realizations of aggregate and idiosyncratic productivity shocks.
3. Firms decide about the prices of their products simultaneously. First, they decide whether to change prices, or not. Second, those firms that have decided to change prices, choose the new prices of their products.

[23] It will be clear in *Section 5* that under demand-supply interactions, many different steady state distributions exist.

[24] Koop et al. (1996) explain in detail why this is the appropriate way of simulating impulse response functions in nonlinear multivariate models.

4. The price level is calculated. As it is clear from demand function (1), it plays an important role in the demand decision of the representative household.
5. The household decides about the demanded quantities of all product varieties given income and prices. Production is demand-determined, thus the demand decision determines the output of each product variety, as well: there are neither inventories, nor shortages of any product variety.
6. Finally, aggregate statistics are calculated in order to characterize the macro-level behavior of the market. The most important aggregate statistics calculated at the end of the period are real aggregate output and the inflation rate. For the sake of easier interpretation, the latter is measured by the year-on-year growth rate of the price level.[25]

3.4. Estimating the Strength of Demand-Supply Interactions

A key parameter determining the extent of long-run monetary non-neutrality in the model is η, the strength of demand-supply interactions. Coming up with a well-founded empirical estimate for the value of η would require a separate, exhaustive econometric study, therefore it is out of the scope of this research. Nevertheless, I try to come up with a simple estimate for η in order to give the model a chance to provide us with some clue about the order of magnitude of long-run monetary non-neutrality in reality.

In order to estimate the parameters of equation (4), it seems necessary to have empirical data about the aggregate component of supply potentials. However, I show in *Appendix C* that it is sufficient to have data about macro-level potential output, if the law of large numbers can be assumed to hold for idiosyncratic productivity shocks, i.e. if they cancel out in the aggregates.[26] The reason for this is that under this assumption, the potential growth rate always equals the growth rate of the aggregate component of supply potentials, hence $\log g_t^{\mu}$ can be substituted with $\Delta \log \bar{Q}_t$, the growth rate of potential output, when estimating equation (4).

I use quarterly data about real GDP and potential GDP from the U.S. to estimate equation (4). Both variables are measured in billions of 2012 dollars, the time series of real GDP is seasonally adjusted, and its source is the U.S. Bureau of Economic Analysis. I use the estimate of the U.S. Congressional Budget Office to measure potential output.[27] As the two empirical distributions characterizing micro-level price changes are based on a dataset that I have aggregated to monthly frequency, a period in the model should correspond to a month, hence η should also be estimated using monthly data. Unfortunately, the highest frequency, at which GDP data are available, is quarterly. Therefore, I use quadratic spline interpolation to approximate the possible monthly time series of real GDP and potential GDP. My estimates are based on this interpolated sample that covers all the months between January 1989 and December 1997 (108 observations altogether), which is the same time period, during which the Dominick's dataset has been collected. As a robustness check, I use a larger sample, as well, which contains interpolated monthly data

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[25] A period in the model will correspond to a month.

[26] This assumption is always made in DSGE-type menu cost models, but it is not a trivial assumption at all. See e.g. Jovanovic (1987), Durlauf (1993), Gabaix (2011) or Acemoglu et al. (2012) for possible explanations why the law of large numbers may not hold for idiosyncratic shocks in reality.

[27] The data are downloaded from the FRED database of the Federal Reserve Bank of St. Louis.

from January 1949 to December 2018 (840 observations altogether). The right-hand side variable in equation (4), the output gap is calculated as the log-difference between actual and potential GDP, and is denoted as $\hat{Q}_t$.

Table 1 contains the results of some augmented Dickey-Fuller (ADF) tests for the presence of a unit root in the time series of the potential growth rate and the output gap. The test equations include an intercept and a deterministic time trend. The optimal lag length is selected according to the Schwarz Information Criterion.

Table 1: The results of augmented Dickey-Fuller tests performed on the growth rate of U.S. potential GDP and on the output gap

Variable	$\Delta \log \bar{Q}_t$	$\hat{Q}_t$	$\Delta \log \bar{Q}_t$	$\hat{Q}_t$
ADF test statistic	-0.5111	-2.5788	-3.7924**	-4.4667***
(p-value)	(0.9816)	(0.2909)	(0.0173)	(0.0018)
Sample	1989-1997	1989-1997	1949-2018	1949-2018
Frequency	Monthly	Monthly	Monthly	Monthly
Number of observations	103	103	826	820

Note: * - significance at $p < 0.10$, ** - significance at $p < 0.05$, *** - significance at $p < 0.01$.

Surprisingly, I am not able to reject the null hypotheses that the time series of the potential growth rate and the output gap contain unit roots based on the 1989-1997 sample. However, I am able to reject them at the 5% significance-level based on the full (1949-2018) sample. This suggests that the two variables are probably stationary, but the time period between 1989 and 1997 is simply too short to be able to reveal their stationary nature. Hence, equation (4) can be estimated using the 1989-1997 sample, but I will estimate it using the 1949-2018 sample, as well, as a robustness check.

Table 2: OLS estimates of the strength of demand-supply interactions and of the standard deviation of aggregate productivity shocks

Dependent variable	$\Delta \log \bar{Q}_t$				
η	0.0192***	0.0183***	-	-	0.0566***
	(0.0013)	(0.0011)			(0.0068)
σ_v	0.0002	0.0007	0.0004	0.0009	0.0006
Constant	Yes	Yes	Yes	Yes	Yes
Sample	1989-1997	1949-2018	1989-1997	1949-2018	1989-1997
Frequency	Monthly	Monthly	Monthly	Monthly	Quarterly
R^2	0.68	0.26	0.00	0.00	0.68
Number of observations	107	839	107	839	35

Note: Standard errors are in parentheses. * - significance at $p < 0.10$, ** - significance at $p < 0.05$, *** - significance at $p < 0.01$.

Table 2 contains the results of estimating equation (4) based on various samples and conditions. A constant term is included in the equation in all cases, but its value is not reported, as $\bar{g}^{\mu}$ will be calibrated later to match the empirical value of the mean nonzero price change, allowing the model to generate realistically high trend inflation. I also report estimates for the standard deviation of aggregate productivity shocks σ_v with and without the restriction that $\eta = 0$. The estimates with $\eta = 0$ will be useful for calibrating model variants, in which I assume away demand-supply interactions. Since the explanatory variable is lagged in equation (4), the estimations can be performed with ordinary least squares (OLS).

The estimate for η seems to be quite robust: it is around 0.02 in the 1989-1997 sample, as well as in the 1949-2018 sample, and it is significantly different from zero at all reasonable significance-levels. This estimate means that a 1% output gap is expected to increase the potential growth rate by 0.02 percentage points next month, which refers to the presence of reasonably weak, but still, statistically significant demand-supply interactions in the U.S. economy. According to the estimation based on the 1989-1997 sample, the output gap is able to explain 68% of the variation in the potential growth rate, which is a remarkably large portion, but it probably overestimates the true explanatory power because of the small sample size and because of the inability of the ADF test to reject the null hypotheses that the two time series contain unit roots. If the large (1949-2018) sample is used, the R^2 decreases to 0.26, which refers to an explanatory power that is easier to believe.

A natural counterargument against the measured significance of demand-supply interactions is that it might be artificially introduced into the sample by interpolating monthly time series from quarterly ones. In order to assess the validity of this counterargument, I reestimate equation (4) using the original quarterly sample, which does not contain interpolated observations. It turns out that η remains significantly different from zero at all reasonable significance-levels, and its value is around three times as large as the one estimated using the interpolated monthly sample, in accordance with the fact that a quarter consists of three months. It is remarkable that the R^2 does not decrease compared to the estimation carried out with the monthly sample in spite of the much smaller number of observations[28] and in spite of the fact that interpolated time series are less volatile than observed ones.

The estimate for the standard deviation of aggregate productivity shocks seems to be quite robust, as well. σ_v does not turn out to be greater than 0.0009 during any of the estimations. Based on the monthly 1989-1997 sample, the standard deviation of aggregate productivity shocks is estimated to be 0.02%, which is a reasonably small value in line with micro-level empirical studies, according to which most of the variation in plant- or firm-level total factor productivity is caused by idiosyncratic shocks, and not by aggregate ones. (Bergoeing et al., 2003; Ábrahám – White, 2006; Bachmann – Bayer, 2013; Castro et al., 2015) However, this value may be underestimated because of the use of interpolated time series that are less volatile than the true ones.

3.5. Calibration

Based on the results of *Section 3.4*, I set the value of η to 0.02 in model variants with demand-supply interactions, while the value of σ_v will be 0.0002 in model variants

[28] However, the small sample size reduces the reliability of p-values, as well.

with demand-supply interactions, and it will be 0.0004 in model variants without demand-supply interactions.

There are some more parameters, which I assign a value to before carrying out the calibration exercise. The length of the simulations (T) and the number of firms (N) are chosen to be as large as it is tolerable from the point of view of the computational burden. Specifically, I set T to 10000 and the number of different product varieties $N \times G$ to 1000. In simple single-product model variants, this is equivalent to setting the number of firms to 1000. In multiproduct model variants, I will assume that $G = 2$, which is the same value as the one used by Midrigan (2011) and Karádi and Reiff (2019). Two goods per firm turn out to be enough for the model to generate a realistic amount of small price changes. If $G = 2$, then $N = 500$ to keep the number of product varieties in the market at the value of 1000.

Following Midrigan (2011), I set the value of the across-firm elasticity of substitution ε to 3 and the value of the across-good elasticity of substitution to 1.1. The former value is based on empirical estimates of the elasticity of substitution in grocery stores similar to Dominick's, while the latter value is motivated by the idea that goods sold by the same firm are probably less substitutable, than the goods sold by competitors.

I measure nominal aggregate demand by the nominal GDP. I again approximate the monthly time series from the quarterly one using quadratic spline interpolation. The data are again seasonally adjusted, and their source is the U.S. Bureau of Economic Analysis.[29] I set the value of the steady state gross growth rate of nominal aggregate demand $\bar{g}^Y$ to 1.0046, which is the average gross monthly growth rate of nominal GDP in the U.S. between 1989 and 1997, the same period, during which the Dominick's dataset has been collected. I estimate the other two parameters of stochastic process (2) governing nominal aggregate demand by fitting an AR(1) process on the monthly growth rate of U.S. nominal GDP. I estimate the persistence of nominal demand growth φ to be 0.61 and the standard deviation of monetary shocks σ_ξ to be 0.0015. These are almost the same values as the ones estimated by Midrigan (2011) using the monthly time series of monetary aggregate M1 to measure nominal aggregate demand.[30] The value of φ is exactly the same, but his estimated value for σ_ξ (0.0018) is slightly greater than mine. A possible reason for this is that I use an interpolated monthly time series for the estimation, which is less volatile than the true one. For my simple model variants, in which I will assume away trend inflation, I reestimate equation (2) with the restriction that $\bar{g}^Y = 1$. Using this restriction, the estimated value of φ turns out to be 0.93, while σ_ξ is estimated to be 0.0017.

There is no consensus in the literature about the value of parameter ρ that determines the persistence of the good-specific component of supply potentials. I follow Costain and Nakov (2011) and Karádi and Reiff (2012), and set its value to 0.95, which leads to highly persistent good-specific components.

The rest of the parameters is calibrated in order to allow the model to match some important moments of the two empirical distributions related to micro-level price changes. I have described the values and the importance of these moments in *Section 2*. Grazzini and Richiardi (2015) argue that among the standard methods used for estimat-

[29] The data are again downloaded from the FRED database of the Federal Reserve Bank of St. Louis.
[30] Karádi and Reiff (2019) also use the same values as the ones estimated by Midrigan (2011).

ing the parameters of DSGE models, the simulated method of moments (SMM) is the easiest to apply in an agent-based framework. Therefore, I calibrate the parameters of my model variants using SMM. According to the central idea of SMM, the estimated combination of parameters is the one that minimizes the average distance between some moments simulated by the model and their empirical counterparts.[31] In particular, I use the unweighted sum of squared log-deviations between the simulated and the empirical values of the moments as a criterion function to be minimized.[32] I use as many moments for calibrating each model variant as the number of parameters to be estimated. This assures that each model variant will be just identified.

Specifically, I use the mean size of price changes and the ratio of the size of price increases to price decreases to pin down the values of the strengths of upward and downward price adjustment, α^U and α^D. The value of the asymmetry parameter θ of price adjustment is pinned down by the fraction of price increases among all nonzero price changes. The mean price adjustment threshold $\bar{z}$ is calibrated to match the mean frequency of price changes, while I use the standard deviation of price adjustment thresholds σ_z to reproduce the skewness of the empirical distribution of the frequencies of price changes. The standard deviation of nonzero price changes is used to calibrate the standard deviation of idiosyncratic productivity shocks σ_ζ, and I allow the model to match the kurtosis of the empirical distribution of price changes by calibrating the probability of nonzero idiosyncratic productivity shocks λ properly. A smaller value of λ increases the kurtosis of the idiosyncratic shock distribution. The within-firm correlation between good-specific productivity shocks ρ_ζ is used to match the fraction of small price changes in the Dominick's dataset, which is measured by the fraction of price changes with a size smaller than half of the mean size of price changes. Smaller correlation between good-specific productivity shocks increases the fraction of small price changes, since the probability of a large shock hitting one of the goods accompanied by a small shock hitting the other good is higher. Under such realizations of good-specific productivity shocks, price adjustment is induced by the large shock, and a small price change is carried out for the good hit by the small shock, which has only been slightly mispriced.

Finally, I use the gross steady state potential growth rate $\bar{g}^\mu$ to match the mean nonzero price change, thereby generating a realistic amount of trend inflation in the model. Higher steady state potential growth reduces trend inflation. The usual practice followed during the calibration of DSGE-type menu cost models with trend inflation is to assume away potential growth and to set the steady state growth rate of nominal aggregate demand equal to the empirical rate of trend inflation. (Golosov – Lucas, 2007; Nakamura – Steinsson, 2010; Karádi – Reiff, 2019) I do not follow this practice because of two reasons:

1. If money is neutral in the long run, then the usual practice is applicable, as the potential growth rate and the rate of trend inflation are independent of each other in the long run. However, if long-run monetary neutrality fails in the model, then these two long-run growth rates become interrelated, hence it is not trivial how the value of the steady state potential growth rate should be chosen under a given

[31] See e.g. Adda – Cooper (2003) for a didactic description about the simulated method of moments.

[32] In case of moments, the values of which are allowed to be negative, I substitute the log-deviation between the simulated and the empirical value of the moment with their relative deviation.

steady state growth rate of nominal aggregate demand to generate the desired rate of trend inflation in the model. The only possibility left is to involve $\bar{g}^{\mu}$ into the SMM estimation and to choose an appropriate empirical moment that helps generating a realistic rate of trend inflation.

2. It is not assured that the inflation rate inherent in the Dominick's dataset is the same as the macro-level inflation rate in the U.S. economy during the same time period. By matching the mean nonzero price change together with some additional moments detailed above, I can assure that the rate of trend inflation produced by the model will be consistent with the empirical dataset, to which it is calibrated.

In *Sections 4-5*, I will analyze several simplified variants of the agent-based menu cost model presented in this section, as well as the fully-fledged model variant. I will discuss the distinguishing features of these model variants in detail in *Sections 4-5*, now I just summarize them in *Table 3* for the sake of transparency. *Table 4* contains the parameter values for each model variant. The values of the parameters that are calibrated during the SMM estimation are underlined. Finally, *Table 5* can be used to assess the model variants' goodness of fit to the empirical data by comparing the values of moments in the empirical data and in the simulated data. The values of the moments that are targeted during the SMM estimation of a given model variant are underlined.

Table 3: Features of the Model Variants

Feature / Model Variant	A0	A	B	C	D	E	F	G
Menu costs	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Heterogeneous menu costs	No	No	Yes	No	No	No	Yes	Yes
Dynamic optimization	No	No	No	Yes	No	No	No	No
Idiosyncratic productivity shocks	No	No	No	No	Yes	Yes	Yes	Yes
Demand-supply interactions	No	No	No	No	No	Yes	No	Yes
Multiproduct firms	No	No	No	No	No	No	Yes	Yes
Trend inflation and asymmetric price adjustment	No	No	No	No	No	No	Yes	Yes
Potential growth	No	No	No	No	No	No	Yes	Yes
Aggregate productivity shocks	No	No	No	No	No	No	Yes	Yes
Leptokurtic idiosyncratic productivity shocks	No	No	No	No	No	No	Yes	Yes

Note: If a cell contains "Yes", then the model variant under consideration contains the corresponding feature. If a cell contains "No", then the model variant does not contain that feature.

I will assess the goodness of fit of the model variants in *Sections 4-5*, but I will not discuss the SMM estimates of the parameter values in detail for each model variant except of the final one, Variant G, which contains all the features presented in this section. According to the estimates presented in *Table 4*, the values of the parameters determining the strength of price adjustment are of intermediate magnitudes with the strength of upward price adjustment α^U being smaller than the strength of downward price adjustment α^D (0.477 versus 0.581). This is not surprising, since I have required the model to reproduce stylized fact 7, according to which price increases are smaller on average than price decreases.

Table 4: Parameter Values of the Model Variants

Notation	Parameter	A0	A	B	C	D	E	F	G
	Assigned Parameter Values								
T	Length of a simulation	10000	10000	10000	10000	10000	10000	10000	10000
N	Number of firms	1000	1000	1000	1000	1000	1000	500	500
G	Number of goods supplied by the same firm	1	1	1	1	1	1	2	2
ε	Across-firm elasticity of substitution	3	3	3	3	3	3	3	3
γ	Across-good elasticity of substitution	-	-	-	-	-	-	1.1	1.1
$\bar{g}^Y$	Steady state gross nominal growth rate	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0046	1.0046
φ	Persistence of monetary shocks	0.93	0.93	0.93	0.93	0.93	0.93	0.61	0.61
σ_ξ	Standard deviation of monetary shocks	0.0017	0.0017	0.0017	0.0017	0.0017	0.0017	0.0015	0.0015
η	Strength of demand-supply interactions	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.02
σ_ν	Std. dev. of aggregate productivity shocks	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0004	0.0002
ρ	Persistence of idiosyncratic prod. shocks	0.00	0.00	0.00	0.00	0.95	0.95	0.95	0.95
$\bar{\pi}$	Maximal profit	-	-	-	1	-	-	-	-
β	Discount factor	-	-	-	0.997	-	-	-	-
	Calibrated Parameter Values								
α^U	Strength of upward price adjustment	1.000	1.000	0.647	-	0.315	0.320	0.480	0.477
α^D	Strength of downward price adjustment	1.000	1.000	0.647	-	0.315	0.320	0.575	0.581
$\bar{z}$	Mean price adjustment threshold	0.000	0.041	0.073	-	0.274	0.270	0.119	0.119
σ_z	Std. deviation of price adjustment thresholds	0.000	0.000	0.010	-	0.000	0.000	0.051	0.050
θ	Asymmetry of price adjustment	0.000	0.000	0.000	-	0.000	0.000	0.355	0.344
$\bar{g}^\mu$	Steady state gross potential growth rate	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0033	1.0038
σ_ζ	Std. dev. of idiosyncratic productivity shocks	0.000	0.000	0.000	0.000	0.121	0.119	0.066	0.066
λ	Probability of a nonzero idiosync. prod. shock	0.000	0.000	0.000	0.000	1.000	1.000	0.046	0.045
ρ_ζ	Within-firm correlation of good-specific productivity shocks	-	-	-	-	-	-	0.557	0.553
$\tilde{z}$	Menu cost	-	-	-	0.0013	-	-	-	-

Table 5: The Values of Targeted and Non-Targeted Moments
in the Empirical Data and in the Data Simulated by the Model Variants

Moment / Model Variant	Data	A0	A	B	C	D	E	F	G
Distribution of Nonzero Price Changes									
Mean (%)	1.9	0.0	-0.2	0.4	0.3	0.4	0.7	1.9	1.9
Mean size (%)	9.7	0.4	4.5	5.2	3.1	10.9	10.9	9.8	9.8
Standard deviation (% points)	12.5	0.5	4.5	5.3	3.2	11.1	11.1	12.4	12.4
Kurtosis	4.28	2.99	1.02	1.12	1.26	1.18	1.20	4.29	4.29
Mean size of price incr. / decr. (%)	81.8	110	101	98.3	106	89.6	90.1	81.4	81.3
Fraction of price increases (%)	66.0	53.2	47.7	53.9	52.7	54.5	55.8	64.7	64.7
Fraction of small price changes (%)	28.9	29.7	0.0	0.0	1.4	0.0	0.0	29.1	29.1
1st decile (%)	2.1	0.1	4.2	4.3	2.2	8.5	8.5	2.1	2.1
1st quartile (%)	3.9	0.2	4.3	4.7	2.5	9.6	9.6	4.4	4.4
Median (%)	7.2	0.3	4.4	5.1	3.0	10.6	10.6	7.6	7.6
3rd quartile (%)	12.0	0.6	4.6	5.7	3.6	12.0	12.0	13.0	13.0
9th decile (%)	22.3	0.8	4.8	6.2	4.1	13.7	13.7	20.3	20.3
Distribution of the Frequencies of Price Changes									
Mean (%)	11.6	100	5.8	7.5	11.6	11.6	11.6	11.6	11.6
Standard deviation (% points)	5.4	0.0	0.0	0.8	0.0	0.3	0.3	5.4	5.3
Skewness	0.62	-	-	0.78	-	0.09	-0.02	0.62	0.62
1st decile (%)	5.1	100	5.8	6.6	11.6	11.3	11.3	4.9	5.1
1st quartile (%)	7.4	100	5.8	6.9	11.6	11.4	11.5	7.3	7.4
Median (%)	11.1	100	5.8	7.4	11.6	11.6	11.6	11.3	11.3
3rd quartile (%)	14.7	100	5.8	7.9	11.6	11.8	11.8	14.9	14.9
9th decile (%)	19.2	100	5.8	8.7	11.6	12.0	12.0	17.9	17.9
An Additional Moment									
Mean year-on-year inflation rate (%)	2.60	0.62	-0.08	0.34	0.42	-0.21	0.20	1.59	1.59

Note: The moments targeted during the calibration of a particular model variant are underlined. The fraction of small price changes is the fraction of price changes that are smaller than half of the mean size of nonzero price changes. In case of the distribution of nonzero price changes, the percentiles refer to percentiles of the size distribution of nonzero price changes. The empirical value of the mean year-on-year inflation rate is the mean year-on-year growth rate of the price level in the U.S. between 1989 and 1997. Inflation is measured by the GDP-deflator.

These values mean that conditional on price adjustment, a 1% positive (negative) difference between the anticipated demand for a product and its supply potential induces a 0.477% (0.581%) price increase (decrease). The mean price adjustment threshold $\bar{z}$ is 11.9%, which means that for the average firm, the weighted average difference between anticipated demand for its products and their supply potentials has to exceed 11.9% in order to induce the firm to adjust the prices of its products. The standard deviation σ_z of price adjustment thresholds across firms is equal to 5 percentage points. The asymmetry parameter θ of price adjustment is 0.344, implying that the weight assigned to products with anticipated excess supply is by 34.4% smaller than the weight assigned to products with anticipated excess demand, when firms are considering whether to change their prices, or not. In steady state, the potential output of the economy grows by 0.38% from month to month, since $\bar{g}^{\mu}$ has turned out to be 1.0038. The standard deviation σ_{ζ} of idiosyncratic productivity shocks is 6.6%, which falls into the standard range of values that can be found in the literature.[33] The probability λ of a nonzero idiosyncratic productivity shock arriving is 0.045, which is again close to the standard values reported in other papers.[34] Finally, the within-firm correlation ρ_{ζ} between good-specific productivity shocks has turned out to be 0.553, which is between the value produced by Midrigan (2011)'s model (0.53) and the value assumed by Karádi and Reiff (2019) (0.60).

4. DO MENU COSTS LEAD TO LONG-RUN MONETARY NON-NEUTRALITY?

4.1. The Basic Model Variants

In this section, I use the agent-based menu cost model presented in *Section 3* to examine whether the first possible post-Keynesian explanation for the empirical evidence against long-run monetary neutrality, nonlinear price adjustment can be justified theoretically and empirically, or not. As I have mentioned in the *Introduction*, nonlinear price adjustment can be motivated by the lack of decreasing returns in the vicinity of the supply potential in a single-product setting, but I stick to the other possible motivation, which is the presence of menu costs related to price adjustment.

My aim in this section is not to get to quantitatively realistic conclusions, but to qualitatively explore the economic mechanisms that lead to, or do not lead to long-run monetary non-neutrality. Therefore, I will start from an extremely simplified variant of the model presented in *Section 3*, and I will introduce new features to it step by step in order to make it clear, which features are responsible for the prevalence or for the failure of long-run monetary non-neutrality. I am going to examine these mechanisms by simulating impulse responses to a permanent monetary shock. I hit the *growth rate* of nominal aggregate demand with a *transitory* shock, which is going to lead to a *permanent* increase in the *level* of nominal aggregate demand. Then, I will observe if there are any forces in the model that will lead real aggregate output back to its initial steady state value in the long run. If there are such forces, then money is neutral in the long run. If there are no such forces, long-run monetary non-neutrality is observed.

The starting point of the analysis is the benchmark model variant labeled as Variant A0. In Variant A0, firms are homogeneous in all respects, all of them supply a single product, and there is no trend inflation, hence price adjustment is symmetric. There is no potential growth, demand-supply interactions are assumed away, and firms are not hit by

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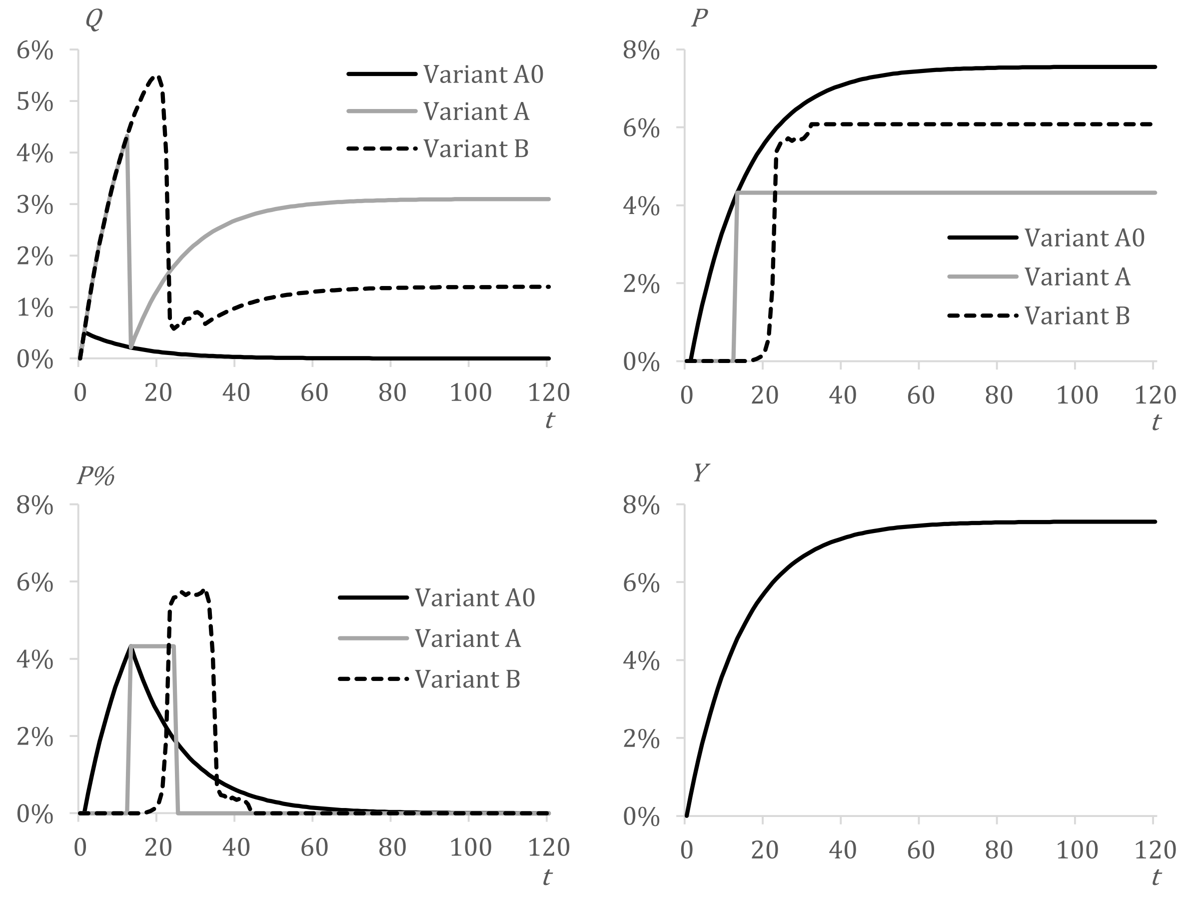
[33] Note that the standard deviation of the good-specific component $\delta_{i,g,t}$ of the supply potential is $\sigma_{\zeta}/\sqrt{1-\rho^2} = 0.210$, i.e. 21.0%.

[34] This probability is 0.030 in Midrigan (2011) and 0.096 in Karádi – Reiff (2019).

any kind of productivity shocks, hence supply potentials are constant in time. Most importantly, price adjustment is free, there are no menu costs to pay.

The impulse responses of this simple model variant to a three standard deviation monetary shock are presented on *Figure 2*.[35] Inflation is denoted by *P%* on the figure. On impact, the monetary shock increases the purchasing power of the household, hence demand increases for all product varieties in the goods market. It can be seen on *Figure 2* that real aggregate output is slightly increased in the short run even in the absence of menu costs. The reason for this is the bounded rationality of firms, because of which they are not able to react to the shock optimally in the short run, hence their actual output increases above their supply potential. But in the long run, they react to the excess demand by increasing their prices. This reduces the household's purchasing power back to its initial level, hence real aggregate demand and output return to their initial steady state values, and the increase in nominal aggregate demand is fully absorbed by the price level. In spite of the slight short-run real effect of the monetary shock, money is neutral in the long run in the absence of menu costs.

Figure 2: The Impulse Responses of Real Aggregate Output, the Price Level and Inflation to a Three Standard Deviation Positive Permanent Shock to the Level of Nominal Aggregate Demand in Model Variants A0, A and B



[35] I hit the model with an atypically large, three standard deviation monetary shock, because under the calibration presented in *Table 4*, a one or a two standard deviation shock would not be sufficiently large in Model Variant B to induce any firms to change their prices.

Long-run monetary non-neutrality emerges in Variant A, which is the extension of Variant A0 with nonlinear price adjustment. Firms are still homogeneous in all respects, but they have to face menu costs when changing their prices, therefore price adjustment thresholds are positive. The economic mechanism behind the observed impulse response of Variant A is the following. In the first few periods, the growth of nominal aggregate demand fully transforms into real output growth, as the presence of menu costs implies that firms do not react to small deviations between demand and the supply potential by changing their prices. But as demand gets too far away from the supply potential, firms become willing to pay the menu cost, and they increase their prices. Real output falls as a consequence, but immediately starts rising again as nominal aggregate demand increases further. This time, actual output does not get far enough from the supply potential to make firms willing to pay the menu cost once more. Hence, prices do not increase anymore, and the level of real aggregate demand becomes permanently higher as nominal aggregate demand settles down at its new, higher steady state level. As a consequence, the quantities of all product varieties are permanently higher in the new steady state than in the initial one. This means that a permanent shock to the level of nominal aggregate demand has a permanent effect on the level of real output, thus money is not neutral in the long run in this simple model variant.

A drawback of Variant A is that discrete jumps can be observed in real output and in the price level, which may be realistic at the micro-level, but not at the macro-level of the economy. The impulse response functions can be made continuous if it is assumed that firms are heterogeneous with respect to their price adjustment thresholds.[36] This assumption is justified by the empirical fact presented on the right panel of *Figure 1*, according to which there is substantial heterogeneity in the frequencies of price changes of different products. Model Variant B is the extension of Variant A with heterogeneous price adjustment thresholds. Long-run monetary non-neutrality is present in this model variant, as well, but the discrete jumps have disappeared from the impulse response functions. The reason for this is that now, individual firms adjust their prices in response to the monetary shock in different time periods, and not at the same time. Still, long-run price adjustment is not perfect in this case, either.

The impulse response functions presented on *Figure 2* make it clear: the presence of menu costs leads to long-run monetary non-neutrality in my basic model variants. This is in line with the results of Dixit (1991) and Delgado (1991), according to which the presence of menu costs results in hysteresis in real output and in the price level. This raises an important question: why is money neutral in the long run in standard DSGE-type menu cost models? (Golosov – Lucas, 2007; Gertler – Leahy, 2008; Nakamura – Steinsson, 2010; Midrigan, 2011; Alvarez et al., 2016; Karádi – Reiff, 2019) DSGE-type menu cost models contain two key assumption that my basic model variants do not, and might potentially eliminate long-run monetary non-neutrality:

1. *Dynamic optimization*: Firms are perfectly rational instead of being boundedly rational. They decide about the optimal prices by solving a dynamic optimization problem.

[36] This idea stems from the models of *strong hysteresis*, in which the aggregation of discontinuous micro-level adjustments to exogenous shocks leads to continuous nonlinear adjustment at the macro level. (Amable et al., 1993, 1994; Göcke, 2002; Setterfield, 2009)

2. *Idiosyncratic productivity shocks*: Besides the monetary shock, which is an aggregate shock affecting all firms, firms are hit by idiosyncratic productivity shocks in each period.

In the next two subsections, I will introduce these two features into Model Variant A separately, and I am going to study how they affect the emergence of long-run monetary non-neutrality. For simplicity, I will assume that firms are homogeneous with respect to their price adjustment thresholds.

4.2. Dynamic Optimization

Let us first turn to the assumption of perfectly rational firms that decide about their prices by dynamic optimization. If one takes a look at *Figure 2*, it can be noticed that the output of firms deviates permanently from the supply potential in the new steady state of Model Variant A, causing infinitely big losses for them in the long run compared to the maximal attainable profit stream under flexible prices. A forward-looking firm may notice this, and may be willing to pay the finite menu cost in the present in order to avoid the infinitely big expected future loss. Thus, it may revert the price back to its flexible price steady state level, eliminating long-run monetary non-neutrality.

Model Variant C is the same as Variant A except of one important difference: firms are perfectly rational instead of being boundedly rational. Instead of using heuristic price decision rule (3), they decide about their prices by dynamic optimization. I assume that firms are perfectly informed about the structure of the market, i.e. they know demand function (1), AR(1) process (2) governing the growth of nominal aggregate demand, as well as the fact that the supply potentials and the menu costs of their competitors are the same as theirs. They do not only possess all relevant information about the state of the goods market, their decision-makers have all the cognitive abilities necessary to make the optimal decision. These simplifying assumptions imply that all firms always set the same price, hence it is sufficient to study the decision problem of one single representative firm. Therefore, it is not necessary to use subscripts i and g to distinguish between different firms and goods in the remainder of this subsection.

The above-mentioned assumptions allow me to simplify the definition of the price level and demand function (1), as well. If all firms set the same price, i.e. $p_{i,t} = p_t$ for $\forall i$, then the CES price index becomes:

$$P_t = N^{\frac{1}{1-\varepsilon}} \cdot p_t.$$

Substituting this into equation (1), the demand function for all product varieties simplifies to:

$$c_t = \frac{Y_t}{Np_t}. \tag{7}$$

Demand function (7) expresses that real aggregate demand is divided equally among the N firms. I maintain the assumption that production is determined by demand, thus $c_t = q_t$ for $\forall t$.

Perfectly rational firms maximize their value, i.e. the present value of their expected stream of profits on an infinite horizon. I assume that the profit function of the representative firm is the following:

$$\pi_t = \bar{\pi} - \left(\frac{q_t - \bar{q}}{\bar{q}}\right)^2 - \tilde{z} \cdot I(p_t \neq p_{t-1}), \tag{8}$$

where π is the amount of profits earned by the firm, $\bar{\pi}$ is the maximal attainable profit level, i.e. the amount of profits under flexible prices, $\tilde{z}$ is the menu cost, which is not the same as the price adjustment threshold z in price decision rule (3), and $I(\,)$ is again the indicator function, but now, it returns the value of 1, if the firm changes the price, and it returns the value of 0, if the firm keeps the price unchanged. For simplicity, I call equation (8) the profit function, but it would probably be more appropriate to call it the payoff function, since π is not the exact amount of profits measured in dollars, just some kind of a payoff that is proportional to the profit earned by the firm. Still, it will not lead to any confusion, if I call it the profit function, since maximizing the payoff is equivalent to maximizing the amount of profits.[37]

Profit function (8) expresses that the firm earns the maximal $\bar{\pi}$ amount of profits, if its output is equal to its supply potential, and it does not change the price, hence it does not have to pay the menu cost. The larger the relative difference between output and the supply potential, the less profits are earned. The deviation can be of any direction: if output is lower than the supply potential, then the firm will not earn as much revenue as it would in case of producing at the level of the supply potential. If output is higher than the supply potential, then the firm will have to overuse its capacities, causing its costs to rise by too much, and implying a smaller amount of profits compared to $\bar{\pi}$. Besides the deviation of output from the supply potential, the menu cost also decreases the amount of profits in case of a price change.

In order to make the firm's dynamic profit maximization problem solvable, it has to be formulated in terms of stationary variables. The decision variable of the firm is the price, but as nominal aggregate demand is not stationary, the price will not be stationary, either. Therefore, I use output as the control variable, since its stationarity is assured by the constancy of the supply potential, which serves as a "center of gravity" for actual output. Of course, the firm does not decide about its output directly, but demand function (7) represents a one-to-one relationship between the price and the output, hence the choice of output unambiguously determines the price to choose, as well. Although the formal control variable of the firm is output, the fixed adjustment cost is still attributed to changing the price, and not to changing the amount of output. As the dynamic optimization problem of the firm is now stationary, I drop time indices in order to simplify the notation. This can be done, because the firm solves an infinite-horizon optimization problem of the same structure in every period. In the rest of this subsection, primes will indicate the values of the variables in the next period.

The value of changing the price can be written as:

$$V^C(g^Y) = \max_q \left\{ \bar{\pi} - \left(\frac{q - \bar{q}}{\bar{q}}\right)^2 - \tilde{z} + \beta \mathbb{E}_{g^{Y\prime}|g^Y} V(q, g^{Y\prime}) \right\}, \tag{9}$$

[37] A similar formula is often used in simple menu cost models to approximate the profit function. However, the quadratic loss is usually expressed as a function of the difference between the price and its desired value, and not as a function of the difference between output and its desired value as in equation (8). (Dixit, 1991; Ball – Mankiw, 1994; Karádi – Reiff, 2019) Such a formula can be derived as a second-order approximation of the true profit function. (Alvarez et al., 2016)

where $V^C(g^Y)$ is the value of changing the price, which is a function of only one state variable, the growth rate of nominal aggregate demand. $\beta \in (0,1)$ denotes the discount factor, $V(q, g^{Y\prime})$ is the value of the firm in the next period and $\mathbb{E}_{g^{Y\prime}|g^Y}$ is the conditional expected value operator, where the expected value is calculated conditional on the nominal demand growth of the current period.

For formulating the value of not changing the price, it has to be determined what the output of the firm will be equal to in this case. Let q^{pre}, p^{pre} and Y^{pre} denote the values of output, the price and nominal aggregate demand in the previous period, respectively. If the firm does not change the price, then $p = p^{pre}$. It is also known that $Y = Y^{pre} \cdot g^Y$ by definition. Using these relationships, demand function (7) and the assumption of demand-determined output, the output in case of not changing the price can be written as:

$$q = \frac{Y}{Np} = \frac{Y^{pre} \cdot g^Y}{Np^{pre}} = q^{pre} \cdot g^Y.$$

Substituting this into profit function (8) and using the fact that no menu cost has to be paid, if the firm keeps the price unchanged, the value of not changing the price can be formulated as:

$$V^{NC}(q^{pre}, g^Y) = \bar{\pi} - \left(\frac{q^{pre} \cdot g - \bar{q}}{\bar{q}}\right)^2 + \beta \mathbb{E}_{g^{Y\prime}|g} V(q^{pre} \cdot g^Y, g^{Y\prime}), \tag{10}$$

where $V^{NC}(q^{pre}, g^Y)$ is the value of not changing the price, which is a function of two state variables: previous period output and the growth rate of nominal aggregate demand.

The value of the firm is the maximum of the values of changing and not changing the price:

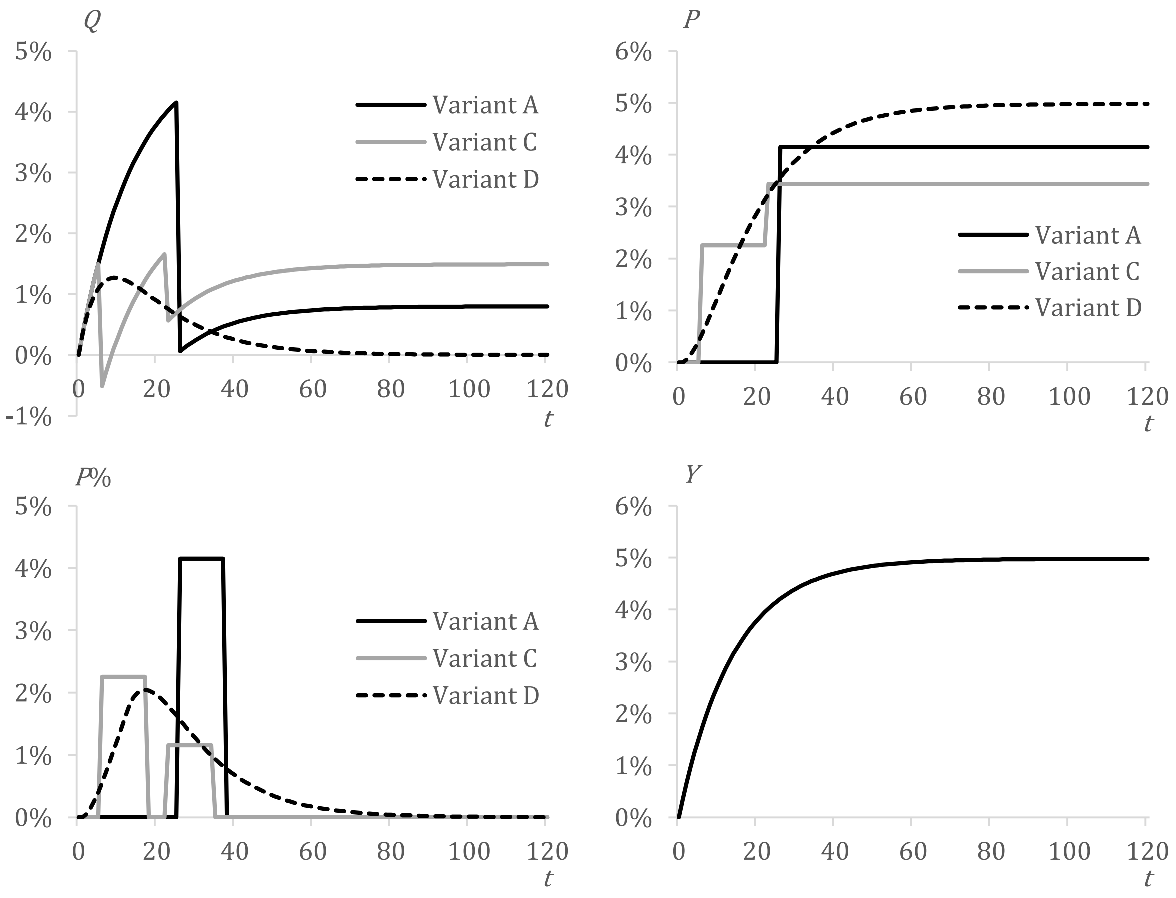
$$V(q^{pre}, g^Y) = \max_{\{C,NC\}} \{V^C(g^Y), V^{NC}(q^{pre}, g^Y)\}, \tag{11}$$

Equations (9), (10) and (11) constitute a system of Bellman equations. I solve this system numerically, using value function iteration on a grid. I approximate AR(1) process (2) of nominal demand growth with a 101-state Markov chain using a modified version of Tauchen (1986)'s method described by Adda and Cooper (2003). Along the dimension of the other state variable, previous period output, the grid consists of 501 elements, and the grid points are equidistantly spaced within the $\pm 25\%$ environment of the flexible price steady state output. I use the same set of values as the control space of current period output. The solution of the (9)-(10)-(11) system of functional equations equips one with the value functions and the policy function of output. For evaluating the value functions and the policy function between and outside of the grid points, I use cubic spline interpolation during the value function iteration and during the simulations. The optimal amount of output can be obtained directly from the policy function, while the optimal price is calculated from demand function (7) given the value of optimal output and using the assumption that output is equal to consumption. Further details about the solution method and the resulting policy function can be found in *Appendix D*.

Following Midrigan (2011), I set the value of the annual discount factor to 0.96, which is consistent with a 4.2% annual interest rate. This implies that the value of the monthly discount factor β will be $0.96^{1/12} = 0.997$. The maximal amount of profits $\bar{\pi}$ is set to 1. The value of the menu cost $\tilde{z}$ is estimated by SMM to match the mean frequency of price changes in the empirical data. It turns out to be 0.0013.

The impulse responses of Model Variants A and C to a two standard deviation positive monetary shock can be compared with the help of *Figure 3*.[38] Despite the preliminary expectations, the assumption of dynamically optimizing firms does *not* eliminate long-run monetary non-neutrality: the long-run real effect of the monetary shock is positive in Variant C, as well. The reason for this is that firms discount their expected future streams of profit during their price decisions. Firms have to suffer infinitely big losses compared to the maximal expected profit stream under flexible prices, since their output deviates permanently from their supply potentials after nominal aggregate demand settles down at its new steady state level. But after discounting, the present value of these losses becomes finite. Therefore, if the difference between actual output and the supply potential is not too big, it is not optimal to pay the finite menu cost in the present in order to avoid expected losses in the distant future that may not even realize at all. This means that the assumption of dynamically optimizing firms cannot be the reason why money is neutral in the long run in DSGE-type menu cost models.

Figure 3: The Impulse Responses of Real Aggregate Output, the Price Level and Inflation to a Two Standard Deviation Positive Permanent Shock to the Level of Nominal Aggregate Demand in Model Variants A, C and D



[38] A one standard deviation shock is not large enough to induce the firms in Model Variant A to change their prices. A two standard deviation shock is atypically, but not unrealistically large.

4.3. Idiosyncratic Productivity Shocks

Let us turn to the other standard assumption of DSGE-type menu cost models, according to which firms are hit by idiosyncratic productivity shocks at the micro level. Model Variant D is another extension of Variant A: firms are boundedly rational again, their price adjustment thresholds are homogeneous, but now, their supply potentials are hit by idiosyncratic productivity shocks in each period. In Variant D, these shocks are assumed to be normally distributed for simplicity.[39]

The impulse responses of Variant D to a two standard deviation positive monetary shock can also be seen on *Figure 3*. It is unambiguous that the introduction of idiosyncratic productivity shocks *does* actually eliminate long-run monetary non-neutrality. Firms are expected to be hit by productivity shocks at the micro level, while nominal aggregate demand converges to its new steady state value. Sooner or later, each firm is expected to face an idiosyncratic shock that is large enough to push its supply potential sufficiently far away from anticipated demand to make it worth changing the price. Thus, idiosyncratic productivity shocks are expected to force firms to adjust to the monetary shock perfectly in the long run by changing their prices, hence reverting real aggregate output back to its initial steady state value and eliminating long-run monetary non-neutrality.

In other words, idiosyncratic productivity shocks act as "replacements" for the Calvo fairy in menu cost models in the sense that they smuggle time-dependency back to state-dependent pricing models. Following some period of time, all firms get the opportunity to adjust their prices to monetary shocks, just like in the Calvo (1983) model of sticky price adjustment. Of course, it is an important difference between state-dependent menu cost models and the time-dependent Calvo model that in the former, it is not randomly determined, which firms get the opportunity for price adjustment. But from the point of view of perfect price adjustment in the long run, both types of models are essentially the same, if idiosyncratic productivity shocks are introduced to state-dependent models.

The results presented in this section make it clear that the reason why there is long-run monetary neutrality in DSGE-type menu cost models is that the menu cost assumption is complemented with another key assumption, according to which firms are hit by idiosyncratic productivity shocks. The results have also provided an answer to the question why the menu cost models of Dixit (1991) and Delgado (1991) do produce hysteresis: although they contain dynamically optimizing firms, these firms are not hit by idiosyncratic productivity shocks.

4.4. Empirical Evaluation

So far, I have presented three model variants with menu costs that produce long-run monetary non-neutrality, and one that does not. If one would like to find out whether the long-run non-neutrality of money is an empirically relevant economic phenomenon, one has to assess how the different model variants fit to the important moments of the two empirical distributions related to price changes.

Table 5 presents the values of these moments in the empirical data, as well as in the different model variants. It can be seen that Model Variants A0, A and B are too simple

[39] The probability of a nonzero productivity shock arriving is $\lambda = 1$.

to be able to match even the targeted moments, not mentioning the non-targeted ones. Variant C matches the targeted moment (the mean frequency of price changes) perfectly, but it suffers from the usual weakness of menu cost models without idiosyncratic productivity shocks: it produces too small price changes. Variant D does a much better job in matching the mean size and the standard deviation of price changes thanks to the introduction of idiosyncratic productivity shocks, but it is still not able to capture many of the important non-targeted moments, including the kurtosis of the distribution of nonzero price changes, as well as the fraction of small price changes. It is not able to reproduce any of the moments of the frequency distribution of price changes except of its mean, since firms are assumed to be homogeneous with respect to their price adjustment thresholds.

It can be concluded that none of the model variants developed so far is capable of matching all important empirical moments concerning price changes. Therefore, some richer model variants need to be built up. However, idiosyncratic productivity shocks need to be a key ingredient of those model variants, as well, since the empirical performance of Variant D has made it clear that they are necessary for the model to reproduce the large mean size of empirical price changes. The importance of idiosyncratic productivity shocks is also stressed by numerous empirical estimates, according to which most of the variation observed in firm- or plant-level productivity is due to idiosyncratic factors. (Bergoeing et al., 2003; Ábrahám – White, 2006; Bachmann – Bayer, 2013; Castro et al., 2015) According to the estimates of Castro et al. (2015), idiosyncratic shocks were responsible for around 80% of the fluctuations in total factor productivities (TFPs) of U.S. manufacturing plants between 1972 and 1997. If idiosyncratic productivity shocks are present in a menu cost model – and demand-supply interactions are absent –, then it produces long-run monetary neutrality. Thus, I conclude that theoretically, it is possible to build models, in which the presence of menu costs leads to long-run monetary non-neutrality, but these models are not plausible empirically. Hence, nonlinear price adjustment, as the first possible post-Keynesian explanation for the empirical evidence against long-run monetary neutrality is theoretically compelling, but its empirical relevance seems to be ambiguous.

5. DO DEMAND-SUPPLY INTERACTIONS LEAD TO LONG-RUN MONETARY NON-NEUTRALITY?

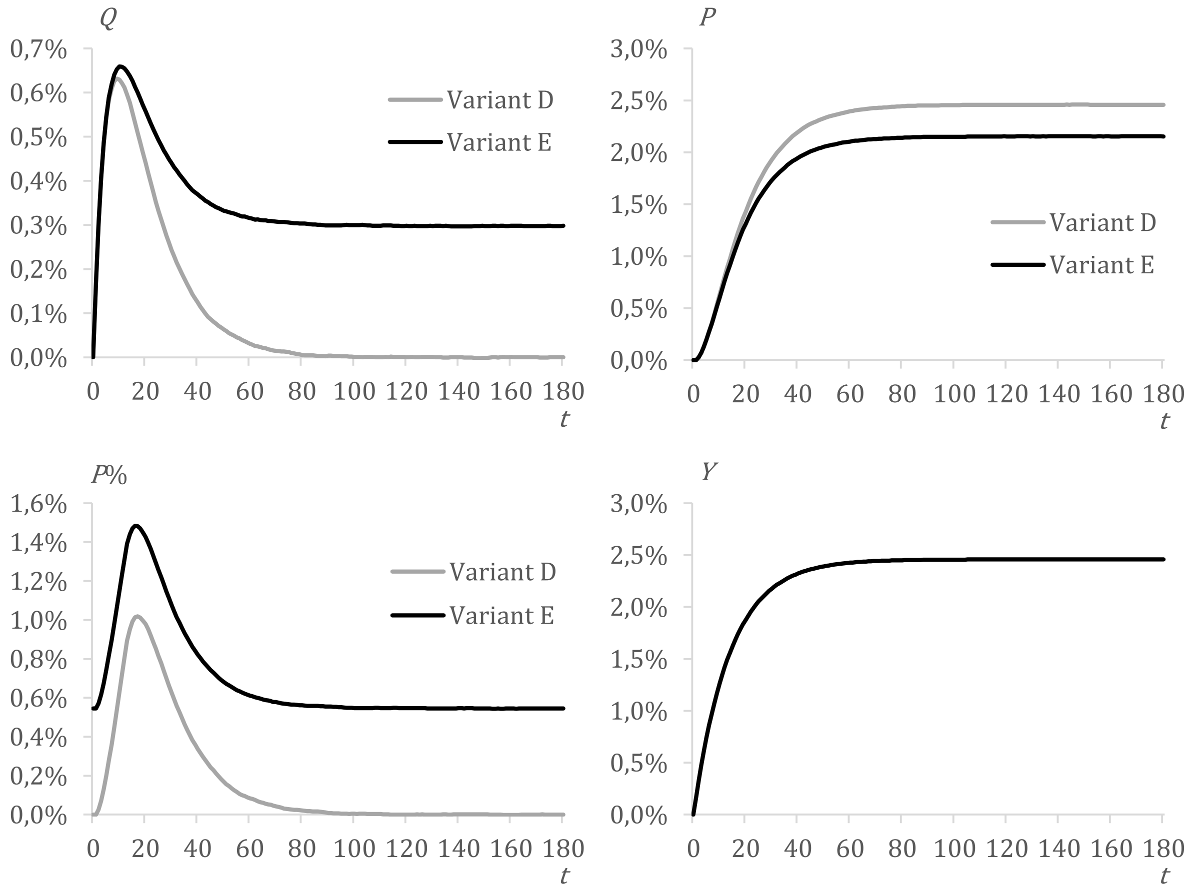
5.1. Inspecting the Mechanism

In this section, I turn to analyzing the second post-Keynesian explanation for the empirical evidence against long-run monetary neutrality, which is the presence of demand-supply interactions in the economy. I will again start with a simplified model variant, with the help of which it will be easier to inspect the economic mechanism, through which demand-supply interactions might lead to long-run monetary non-neutrality. If long-run monetary non-neutrality turns out to be present in the model variant, then I will turn on all the features of the agent-based menu cost model presented in *Section 3* to get a rough estimate about the possible extent of long-run monetary non-neutrality in reality.

As a starting point, I maintain the assumptions about the presence of menu costs and idiosyncratic productivity shocks, as the results of *Section 4* have made it clear that they are necessary for the model to reproduce the mean frequency and the mean size of empirical price changes. Based on the impulse responses produced by Model Variant D, one can be sure that if a model variant with menu costs, idiosyncratic productivity shocks and demand-supply interactions produces long-run monetary non-neutrality, then it has to be the result of demand-supply interactions, and not of menu costs or idiosyncratic productivity shocks.

Model Variant E is the same as Variant D with the exception that demand-supply interactions are turned on. *Figure 4* can be used to compare the impulse responses of the two model variants to a typical – one standard deviation – positive monetary shock.

Figure 4: The Impulse Responses of Real Aggregate Output, the Price Level and Inflation to a One Standard Deviation Positive Permanent Shock to the Level of Nominal Aggregate Demand in Model Variants D and E



The impulse responses of Variant E make it clear that demand-supply interactions reintroduce long-run monetary non-neutrality into the model even in the presence of idiosyncratic productivity shocks. The monetary shock increases nominal aggregate demand, which leads to an increase in the purchasing power of the household in the presence of sticky price adjustment. Hence, real aggregate demand and output rise in the short run, thereby generating a positive output gap. The positive output gap leads to increasing potential output through the mechanisms of demand-supply interactions, which have been detailed in the *Introduction*. As nominal aggregate demand converges to its new steady state level, more and more firms are expected to hit their price adjustment thresholds because of the interplay between increasing nominal demand and idiosyncratic productivity shocks. The unfolding process of price adjustment increases the price level, thereby reducing real aggregate demand and output. However, firms do not adjust to the same supply potentials as the ones prevalent before the arrival of the monetary shock, but they adjust to permanently higher ones. The result is that real aggregate output settles down at a permanently higher steady state value compared to the initial one, meaning that a permanent shock to the level of nominal aggregate demand has a permanent effect on the level of real aggregate output, hence money is not neutral in the long run.

If it is taken into account that I have found some empirical evidence for the significance of demand-supply interactions in *Subsection 3.4*, then the introduction of demand-supply interactions into the model already improves its empirical performance. However, if one takes a look at *Table 5*, it can be seen that the introduction of demand-supply interactions has not improved the model's fit to the empirical moments at all. The empirical performance of Variant E suffers from the same deficiencies as that of Variant D.

In addition, the bottom left panel of *Figure 4* unveils another empirical deficiency of Variant E: it produces steady state inflation even in the absence of trend growth in nominal aggregate demand. This seems to be puzzling at first sight, but it can be explained by the fact that demand-supply interactions transform the time series of real aggregate output into a unit root process. (Amable et al., 1993; Setterfield, 2009) The positive feedback between actual and potential output leads to either self-reinforcing growth, or self-reinforcing decline in these two variables depending on the parameterization. Under the calibration presented in *Table 4*, there is a trend decline in actual and potential output, which is unambiguously unrealistic, since real aggregate output does not converge to zero in real-life economies. In the absence of trend growth in nominal aggregate demand, the trend decline in aggregate output is consistent with a trend growth in the price level: this is why inflation is positive in steady state. Notwithstanding the unrealisticness of these results, they are still able to highlight the fact that in the presence of long-run monetary non-neutrality, real and nominal growth are not independent of each other in the long run.

I conclude that demand-supply interactions, as the second possible post-Keynesian explanation for the empirical evidence against long-run monetary neutrality may be able to serve as a theoretically, as well as an empirically plausible explanation. But the fit of Model Variant E to the empirical moments related to micro-level price changes is still not satisfying enough, therefore it needs to be extended with some additional features to make it able to come up with a picture about the possible extent of long-run monetary non-neutrality in reality.

5.2. The Extent of Long-Run Monetary Non-Neutrality

In this subsection, I analyze two fully-fledged variants of the agent-based menu cost model presented in *Section 3*. Variant F contains all the presented features of the model except of demand-supply interactions. Variant G is the same as Variant F with demand-supply interactions turned on. I have two goals with these two model variants. On the one hand, I would like to examine if a rich specification of my model with demand-supply interactions is able to fit to the empirical data at least as well as an equally rich specification without demand-supply interactions. On the other hand, I would like to come up with an estimate for the possible extent of long-run monetary non-neutrality in reality.

Specifically, Variants F and G contain the following features in addition to those already present in Variants D and E:

- I reintroduce heterogeneity in the price adjustment thresholds in order to allow the simulated distribution of the frequencies of price changes to fit to its empirical counterpart.
- I introduce multiproduct firms in order to allow the model to produce a sufficient amount of small price changes. Introducing within-firm correlation between good-specific productivity shocks helps fine-tuning the fraction of small price changes in the model.
- I introduce trend growth in nominal aggregate demand in order to allow the model to generate a realistic rate of trend inflation. Firms are aware that the trend growth rate of the price level is positive, hence price adjustment becomes asymmetric: $\theta > 0$ and $\alpha^U \neq \alpha^D$.
- I introduce potential growth, i.e. trend growth in the aggregate component of supply potentials, which helps calibrating the model in a way that allows it to produce a trend inflation rate consistent with the Dominick's dataset.
- I allow for the presence of aggregate productivity shocks besides idiosyncratic ones in order to get a more realistic picture about the evolution of supply potentials.
- I assume that the probability distribution of idiosyncratic productivity shocks is leptokurtic instead of being normal, i.e. normally distributed shocks arrive infrequently, according to a Poisson process. This allows the model to reproduce the kurtosis of the empirical distribution of nonzero price changes, thereby tuning the strength of the selection effect in response to monetary shocks to a realistic extent.

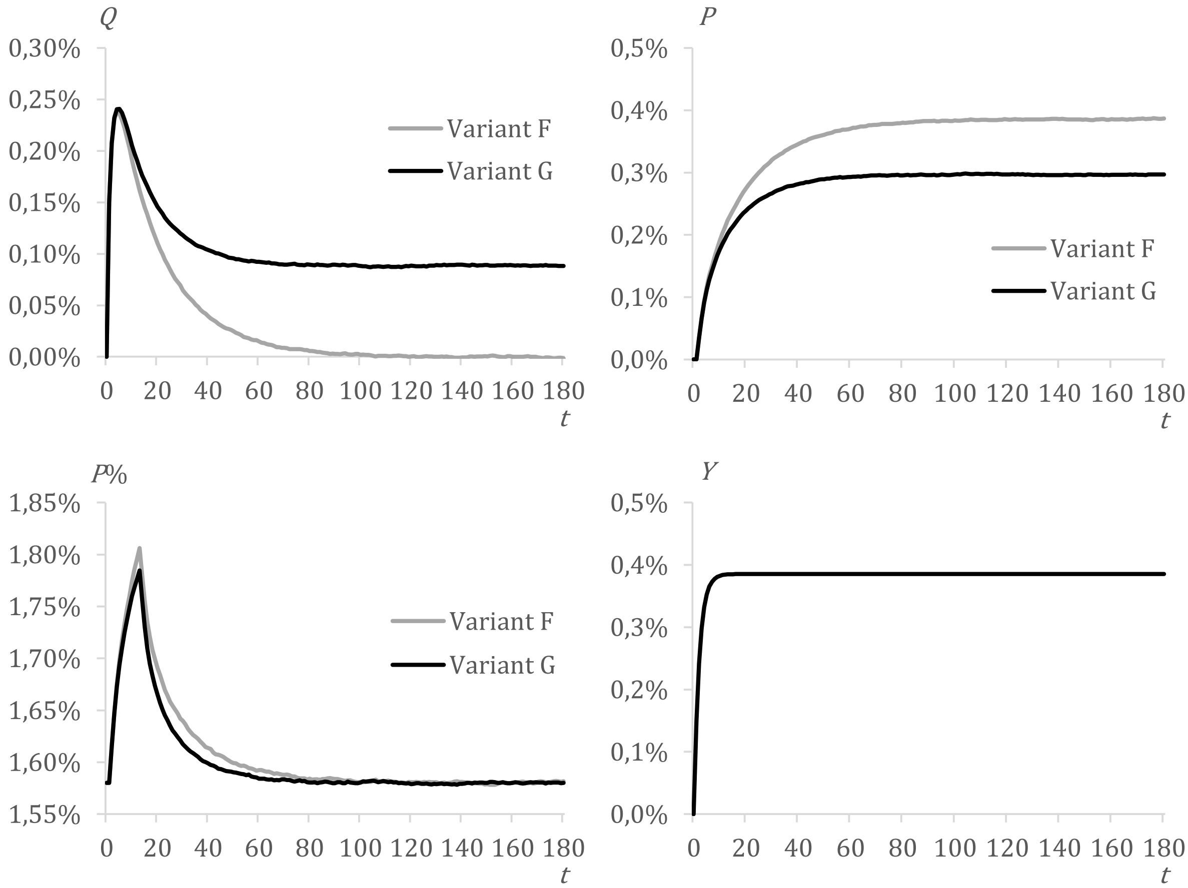
It can be seen in *Table 5* that both fully-fledged model variants are able to match all the targeted moments of the two empirical distributions almost perfectly. I also report some of the most important quantiles of the two distributions in *Table 5*. These are not targeted during the SMM estimation, but the two model variants are still able to match them sufficiently well. This indicates that the model variants are able to reproduce the whole shapes of the two distributions sufficiently well, not just some its moments targeted during the estimation. The mean year-on-year inflation rate is 1.59% in both model variants, which is by around 1 percentage point below the mean annual inflation rate in the U.S. between 1989 and 1997, which is measured to 2.60% by the GDP-deflator. However, this is not necessarily a deficiency of the model, since the rate of trend inflation inherent in the Dominick's dataset is possibly different than the general rate of trend inflation in the U.S. during the time period when the Dominick's dataset has been collected. It may be the case that the trend inflation rate of typical goods sold in grocery stores has been lower between 1989 and 1997 than the general rate of trend inflation in the U.S.[40] Nevertheless, the 1.59% trend inflation rate produced by Model Variants F and G can be considered as

[40] The large number of missing values make it impossible to calculate what the trend inflation rate inherent in the Dominick's dataset is. An alternative would be to calculate the mean annual growth rate of the producer price index for grocery stores, but unfortunately, the earliest year, for which the U.S. Bureau of Labor Statistics reports the value of the producer price index for grocery stores is 2003, which falls out of the time period, during which the Dominick's dataset has been collected (1989-1997).

being of a realistic magnitude. To sum up, the empirical fit of Variants F and G can be considered to be satisfying, hence they are suited to come up with an estimate about the extent of long-run monetary non-neutrality in the U.S. during a normal time period, such as the one between 1989 and 1997.

Figure 5 presents the impulse responses of the two fully-fledged model variants, F and G to a one standard deviation positive monetary shock. Money is not neutral in the short run in Variant F, but it is neutral in the long run, since demand-supply interactions are assumed away. However, they are present in Variant G, hence it produces long-run monetary non-neutrality. A one standard deviation monetary shock is equivalent to a 0.15 percentage point transitory shock to the growth rate of nominal aggregate demand and to a 0.39% permanent shock to the level of nominal aggregate demand. After the path of nominal aggregate demand has reached its new steady state level, the path of real aggregate output is expected to settle down to a new steady state level that is 0.09% higher than on the baseline path. The path of the price level is expected to converge to a new steady state level, which is by 0.30% above the baseline.

Figure 5: The Impulse Responses of Real Aggregate Output, the Price Level and Inflation to a One Standard Deviation Positive Permanent Shock to the Level of Nominal Aggregate Demand in Model Variants F and G



Summing up the results obtained so far in this subsection, the fully-fledged model variant with demand-supply interactions (Variant G) fits to the empirical distributions equally well as the fully-fledged model variant without demand-supply interaction (Variant F). If I take into account the fact that in *Subsection 3.4*, I have managed to come up with some empirical evidence for the significance of demand-supply interactions, Variant G can be considered as even more relevant empirically than Variant F. In Variant G, money is not neutral in the long run, hence I conclude that the presence of demand-supply interactions as the second possible post-Keynesian explanation for the empirical evidence against long-run monetary non-neutrality is not just a theoretically interesting phenomenon, but it is compatible with the empirical observations, as well.

Is the extent of long-run monetary non-neutrality produced by Variant G economically significant? To answer this question, I have to come up with an index, which measures the extent of the long-run real effect that the monetary shock exerts on real aggregate output. I measure the long-run real effect by an index that I call the "long-run pass-through to output". It expresses the fraction of the monetary shock that is "passed through" to real aggregate output in the long run.

To construct the index, remember that the CES price index and the CES quantity index used to measure the price level and real aggregate output, respectively are constructed in a way, which assures that the product of the price level and real aggregate output is equal to nominal aggregate demand:

$$P_t \cdot Q_t = Y_t.$$

If one writes down this equation for the baseline path, as well as for the path induced by the monetary shock, and divides the latter equation by the former, then after some manipulations, one gets

$$(1 + IRF_t^P)\left(1 + IRF_t^Q\right) = (1 + IRF_t^Y),$$

where IRF_t^X is the value of the impulse response function for variable X, t periods after period 0, which is the period preceding the arrival of the shock.

By taking the logarithm of both sides, one gets

$$\log(1 + IRF_t^P) + \log\left(1 + IRF_t^Q\right) = \log(1 + IRF_t^Y).$$

Let us denote the long-run pass-through to output by $LRPT^Q$. It is calculated as

$$LRPT^Q = \frac{\log\left(1 + IRF_\infty^Q\right)}{\log(1 + IRF_\infty^Y)},$$

which is exactly the fraction of the monetary shock that is expected to be absorbed by real aggregate output on an infinite horizon, i.e. in the long run. In practice, I approximate IRF_∞^X by IRF_{300}^X for any variable X. 300 periods are always sufficient for the model get close enough to a steady state after the arrival of the monetary shock.[41]

In case of a one standard deviation positive monetary shock hitting Model Variant G, the long-run pass-through to output is equal to 0.2308, which means that 23.08% (around one quarter) of a typical positive monetary shock is absorbed by real aggregate output in the long run, while the remaining 76.92% (around three quarters) is absorbed by the price level. This suggest that the long-run real effects of monetary shocks must have been substantial in the U.S. between 1989 and 1997, which can be considered as a normal time period. The estimated long-real effect is economically significant, even if one assumes that the long-run pass-through to output is overestimated by 100%, i.e. if it is equal

[41] 300 periods correspond to 300 months, i.e. 25 years in the model.

to only 11.54%. According to these estimates, it seems that long-run monetary non-neutrality is not just a theoretically interesting economic phenomenon, but it is practically important for monetary policy.

Not many empirical estimates can be found in the literature about the extent of long-run monetary non-neutrality. Fisher and Seater (1993) estimate using annual U.S. data from the time period 1869-1975 that a 1% permanent increase in the level of money supply is expected to lead to a 0.5% permanent increase in real GDP. Atesoglu (2001) estimates a cointegrating vector between money supply and real income using annual U.S. data from the time period 1875-1998, and finds that the long-run coefficient of money supply is around 0.5. Both estimates suggest that the long-run pass-through to output must be around 50% empirically, implying that my model underestimates the real effects of monetary shocks compared to the two cited empirical studies. However, note that the elements of the cointegrating vector cannot be interpreted as estimates for the extent of causal effects, as the cointegrated variables are endogenous. (Enders, 2015) De Grauwe and Costa Storti (2004) carry out a meta-analysis, and estimate that a 1 percentage point increase in the nominal interest rate is expected to decrease real output by 0.16% in the long-run. If one interpreted this result as if the long-run pass-through to output was 16%, then my model would overestimate the long-run real effects of monetary shocks compared to this estimate.

5.3. The Effect of the Shock Size on the Extent of Long-Run Monetary Non-Neutrality

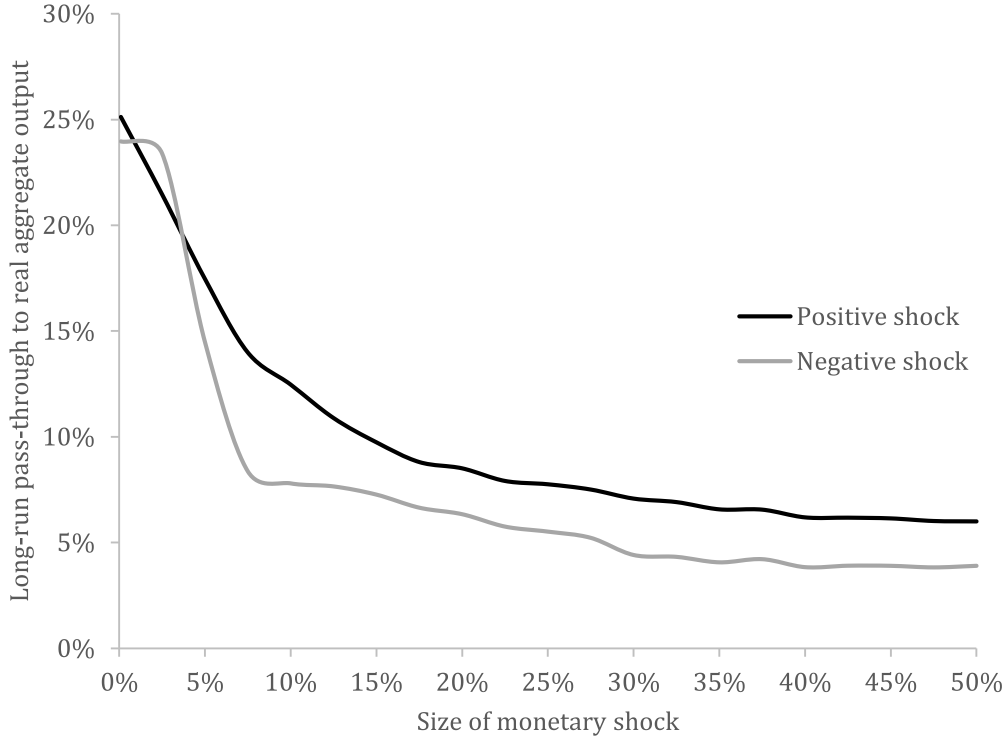
So far, my results suggest that I have found the sorcerer's stone for monetary policy: if money is not neutral in the long run, then central banks only need to hit the economy with an infinitely large monetary shock, and real output will rocket to infinity. In this subsection, I show that this is too nice to be true: long-run expansionary monetary policy has some serious limitations. In the next subsection, I will point out another one, as well.

It is not a good idea for a central bank to hit the economy with an infinitely large monetary shock, since the effectiveness of long-run expansionary monetary policy decreases with the size of the shock. This is illustrated by *Figure 6*, which presents the long-run real effect in Model Variant G as a function of the size of the monetary shock for positive and for negative shocks, separately.[42] The long-run real effect is measured by the long-run pass-through to output.

Let us focus on the case of positive shocks first. It is apparent that the larger the monetary shock, the smaller fraction of it is passed through to real output in the long run, thus the effectiveness of long-run expansionary monetary policy decreases with the size of the shock. This also means that the fraction of the shock passed through to the price level in the long run increases with the size of the shock. Hence, the long-run real effects of large monetary expansions are probably too small to be able to compensate for their inflationary effects. This means that it does not seem to be rational for central banks to hit the economy with positive monetary shocks that are too large.

[42] As I have mentioned in *Subsection 3.3*, I have usually simulated 10000 independent replications with different random draws for the productivity shocks to calculate the values of the impulse response functions. For creating *Figure 6*, I have used only 1000 independent replications in order to save computer time.

Figure 6: The Long-Run Pass-Through to Real Aggregate Output
as a Function of the Size of the Monetary Shock in Model Variant G



What are the reasons for the decreasing effectiveness of long-run expansionary monetary policy as a function of the shock size? To answer this question, it will be useful to turn to a well-known finding of the menu cost literature, according to which the *short-run* pass-through of a monetary shock to the *price level* can be decomposed into three components: (Klenow – Kryvtsov, 2008; Costain – Nakov, 2011; Karádi – Reiff, 2012)

1. *Intensive margin*: Desired price changes become larger as a consequence of the monetary shock for all firms, including those that would have changed their prices even in the absence of the monetary shock, those that turn into price adjusters as a consequence of the monetary shock, as well as those that do not change their prices anyway.
2. *Extensive margin*: The fraction of firms that adjust their prices increases as a consequence of the monetary shock, which would lead to stronger macro-level price adjustment, even if desired price changes remained the same.
3. *Selection effect*: The monetary shock alters the composition of price adjusters. New price adjusters are not randomly selected, but firms with higher than average desired price changes turn into price adjusters with a higher probability.

In my model, long-run price adjustment is stronger, if short-run price adjustment is stronger, since equation (4) makes it clear that the long-run real effects of monetary shocks to potential output are determined by the short-run real effects to the output gap. Hence, if one would like to study the determinants of long-run price adjustment, one will have to turn to the three above-mentioned components of short-run price adjustment. Karádi and Reiff (2012) show that as the size of the monetary shock increases, the fraction of the shock that is passed through to the price level because of price adjustment on the intensive margin stays constant. The role of the extensive margin in macro-level price adjustment is negligible for small shock sizes, but it increases nonlinearly as the size of the shock becomes larger. The strength of the selection effect depends crucially on what is assumed about the probability distribution of idiosyncratic productivity shocks. If their distribution is leptokurtic, as in Model Variants F and G, then the selection effect is weak for small sizes of the shock, its importance increases substantially for medium-sized shocks, and it starts decreasing again for large shock sizes.

What happens with the long-run real effects of monetary shocks in Model Variant G, as the size of the shock becomes larger? The fraction of the shock that is passed through to the price level because of price adjustment on the intensive margin stays constant, but the fraction that is passed through because of price adjustment on the extensive margin increases. This means that for larger shock sizes, more firms are induced to adjust their prices in the short run. As a result, the short-run real effect becomes smaller, which leads to smaller long-run real effects through demand-supply interactions. Thus, the key to understand why the effectiveness of long-run expansionary monetary policy decreases with the size of the monetary shock is that the fraction of price adjuster firms is increased by larger monetary shocks.

It is worth noting that although the long-run real effect of a monetary shock decreases with the shock size, it remains positive even for very large shock sizes. The long-run pass-through to output is equal to 6% in case of a 50% positive monetary shock, and it is 5.03% for a 100% positive monetary shock.[43] These long-run real effects are small, but positive. Why do they not disappear for very large shock sizes? The answer can be seen on *Figure 2*. I have discussed in *Subsection 4.1* that monetary shocks have a slight short-run real effect even in Model Variant A0, in which menu costs are assumed away, since firms are not able to react to the shock optimally in the short run because of their bounded rationality. In Variant G, practically all firms react to very large monetary shocks by adjusting their prices in the short run, i.e. price adjustment is perfect on the extensive margin. In this sense, Variant G behaves similarly to Variant A0, if the size of the monetary shock is very large. But price adjustment on the intensive margin is not perfect because of the boundedly rational price decisions of firms. This opens the way for a small short-run real effect to emerge in Variant G even for very large monetary shocks. After demand-supply interactions take place, this small short-run real effect transforms into a small long-run real effect.

5.4. The Asymmetric Long-Run Real Effects of Positive and Negative Monetary Shocks

A considerable amount of empirical evidence suggests that the *short-run* real effects of positive and negative monetary shocks are asymmetric: positive monetary shocks seem to be less effective than negative ones, or not significantly effective at all. (Cover, 1992; De Long – Summers, 1988; Morgan, 1993) This empirical result can be explained by menu cost models with trend inflation: firms are less willing to react to negative monetary shocks than to positive ones, since they can let trend inflation deteriorate their relative prices, thereby adjusting them to the negative monetary shock without having to

[43] The long-run real effect for the latter shock size is not presented on *Figure 6*.

pay the menu cost for a nominal price decrease. There is no such effect in case of positive monetary shocks, since trend inflation acts against the desired relative price increase. As a result, an intermediate range of the shock size emerges, within which firms adjust their prices in case of positive shocks, but they do not adjust them in case of negative shocks.[44] The resulting stronger price adjustment in response to positive monetary shocks leads to a weaker short-run real effect compared to the case of negative monetary shocks. (Ball – Mankiw, 1994; Karádi – Reiff, 2019)[45]

Let us examine if the asymmetry between the short-run real effects of positive and negative monetary shocks survives for the long-run real effects, as well. The long-run pass-through to output in case of positive and negative monetary shocks can be compared on *Figure 6* for different shock sizes. It can be seen that there is actually an intermediate range of the shock size, within which negative monetary shocks are more effective than positive ones, but for smaller and larger shocks, the effectiveness of positive monetary shocks is higher than that of negative ones. The intermediate range of the shock size is around between 1% and 4%. Taking into account that the standard deviation of shocks to nominal aggregate demand is estimated to be 0.15%, the size of the shock is not likely to fall above the lower bound of this intermediate range, but it is not impossible. A 1% monetary shock, i.e. a 1 percentage point change in the growth rate of nominal aggregate demand is equivalent to a 2.6% permanent shock to its level under the estimated value of the persistence parameter of nominal demand growth. Karádi and Reiff (2019) study the effects of 5 percentage point changes in the value added tax rate in Hungary, the inflationary effects of which are proven to be equivalent to 5% permanent shocks to the level of nominal aggregate demand under some simple assumptions. The 4% upper bound of the intermediate range corresponds to a 10.8% permanent shock to the level of nominal aggregate demand, which means that the changes in the VAT rate studied by Karádi and Reiff (2019) can be considered as monetary shocks with a size that falls into the intermediate range, within which negative monetary shocks are more effective than positive ones. However, it seems unlikely to find empirical examples from developed economies for monetary shocks with a size that exceeds the upper bound of the intermediate range, above which the effectiveness of positive monetary shocks becomes higher again than that of negative ones.

How can the asymmetry results be explained? As I have mentioned in *Subsection 5.3*, the role of the extensive margin in the price adjustment to small monetary shocks is negligible. Hence, for small sizes of the shock, the intensive margin dominates price adjustment. But price adjustment on the intensive margin is stronger in response to negative shocks than in response to positive ones, since the strength of downward price adjustment α^D is calibrated to be greater than the strength of upward price adjustment α^U in order to allow the model to reproduce stylized fact 7, according to which the mean size of price decreases is empirically larger than that of price increases. If short-run price adjustment in response to small monetary shocks is stronger for positive shocks than for negative ones, then the short-run real effects of small positive shocks will be larger than those

[44] Of course, if the shock is large enough, price adjustment will take place even in case of a negative shock.

[45] See Florio (2004) for a survey about alternative explanations for the empirical evidence concerning the asymmetric short-run real effects of positive and negative monetary shocks.

of small negative ones. This asymmetry survives after the short-run real effect has been transformed into long-run real effect through demand-supply interactions.

As the size of the monetary shock increases, the extensive margin begins to play a more and more important role in the price adjustment to the shock. However, the shock size, at which it becomes dominant is larger in case of negative shocks than in case of positive ones. If the size of a positive monetary shock starts increasing, the fraction of price adjuster firms will increase together with it immediately. This is not the case for negative monetary shocks. If the size of a negative monetary shock starts increasing, firms wait first for trend inflation to deteriorate their relative prices, allowing them to save on the menu cost of price adjustment. The fraction of price adjuster firms starts increasing only at a larger shock size compared to the case of the positive shock. This leads to the emergence of the mentioned intermediate range of the shock size, within which macro-level price adjustment to negative monetary shocks is weaker than it is to positive ones, hence the long-run real effects of negative shocks are larger.

Above a sufficiently large size of the shock, price adjustment on the extensive margin becomes so strong that almost all firms adjust their prices in response to the shock – in case of positive ones, as well as in case of negative ones. This means that the difference between the extent of price adjustment on the extensive margin in case of positive shocks and in case of negative shocks becomes negligible. In such a situation, the intensive margin determines again the difference between the long-run real effects of positive and negative monetary shocks just like in the case of small shock sizes. Hence, positive monetary shocks become more effective again than negative ones.

The result that small positive monetary shocks are more effective than negative ones is not in line with the empirical evidence cited above.[46] However, downward price adjustment has to be calibrated stronger than upward price adjustment, if one would like to allow the simulated distribution of nonzero price changes to fit to its empirical counterpart. It also has to be mentioned that although the long-run real effects of small positive monetary shocks are larger in the model than those of negative ones, the asymmetry is not large. In case of a 0.1% monetary shock, the long-run pass-through to output is 25.13% if the shock is positive, while it is 23.97% if the shock is negative. The difference is only 1.2 percentage point. Nevertheless, more research is necessary to reconcile the predictions of the model with the empirical evidence regarding the asymmetric real effects of positive and negative monetary shocks. An interesting possibility is to assume that demand-supply interactions are stronger in case of negative demand shocks than in case of positive ones. There is a little empirical evidence suggesting that this might be true in reality. (Ball, 2009) This assumption would help the model to produce larger *long-run* real effects in response to small negative monetary shocks, but it would not lead to different predictions concerning the asymmetry between the *short-run* real effects of monetary shocks.

[46] However, note that the empirical evidence is about the asymmetry between the *short-run* real effects of positive and negative monetary shocks, and not about the asymmetry between their *long-run* real effects, which are in my focus.

6. CONCLUDING REMARKS

I have developed an agent-based menu cost model to study whether two potential post-Keynesian explanations, nonlinear price adjustment – interpreted to be equivalent with the presence of menu costs related to price adjustment, for simplicity – and the presence of demand-supply interactions are able to serve as theoretically and empirically plausible explanations for the empirical evidence against long-run monetary neutrality. I have assessed the empirical plausibility of the explanations by calibrating my model variants to match some important moments of two empirical distributions related to micro-level price changes, the distribution of nonzero price changes and the distribution of the frequencies of price changes, and by analyzing if the model variants are able to reproduce some key moments of these empirical distributions sufficiently well. The empirical distributions have been derived from micro-level scanner data about the prices of products sold in a particular store of the Dominick's Finer Foods retail chain in the Chicago area. The dataset has been collected between 1989 and 1997, which can be considered as a normal time period in the U.S. economy, hence my estimates for the long-run real effects of monetary shocks can be thought of as valid during normal times.

I have found that it is theoretically possible to come up with model variants, in which the presence of menu costs leads to long-run monetary non-neutrality, regardless of whether firms are assumed to be boundedly or perfectly rational (using a heuristic price decision rule, or optimizing dynamically): if firms never adjust their prices perfectly to monetary shocks in the short run, and they are not hit by any other exogenous shock that would force them to adjust their prices further, then price adjustment cannot be perfect in the long run, either. However, these model variants are not able to fit to the empirical data well. I have shown that the introduction of idiosyncratic productivity shocks into the model eliminates long-run monetary non-neutrality, as these shocks force the firms to adjust their prices perfectly to monetary shocks in the long run. Idiosyncratic productivity shocks are necessary for the model to reproduce the large mean size of empirical price changes. Thus, nonlinear price adjustment as the first post-Keynesian explanation for long-run monetary non-neutrality has been found to be compelling theoretically, but its empirical relevance seems to be ambiguous.

However, the presence of demand-supply interactions as the second post-Keynesian explanation for long-run monetary non-neutrality has been found to be relevant not just theoretically, but empirically, as well. The introduction of demand-supply interactions into the agent-based menu cost model has resurrected long-run monetary non-neutrality even in the presence of idiosyncratic productivity shocks. The short-run real effects of monetary shocks emerging as a consequence of imperfect price adjustment and boundedly rational price decisions transform into long-run real effects through demand-supply interactions, which are modeled as a positive feedback from the output gap to the potential output of the economy.

I have developed a fully-fledged calibrated variant of my model that fits to both empirical distributions related to price changes sufficiently well, and contains demand-supply interactions, hence it can be used to produce a rough estimate for the extent of long-run real effects of monetary shocks in the U.S. economy. According to this estimate, around one quarter of a typical – one standard deviation – positive monetary shock is absorbed by real aggregate output in the long run, while the remaining three quarters are absorbed by the price level. This suggests that long-run monetary non-neutrality is not just a theoretically interesting economic phenomenon, but monetary policy may have substantial long-run real effects in reality, as well.

I have pointed out that long-run expansionary monetary policy has some serious limitations. Its effectiveness decreases with the size of the monetary shock, and its inflationary effects increase disproportionately. The reason for this is that the fraction of firms that adjust their prices in the short run in response to the monetary shock increases with the shock size. This eliminates an increasing part of the short-run real effect, and thereby of the long-run real effect, as well. I have also shown that there is an intermediate range of the shock size, within which negative monetary shocks are more effective in the long run than positive ones, i.e. it is easier for central banks to hurt the real economy in the long run than to stimulate it. The reason for this is that firms are less likely to adjust their prices to negative monetary shocks than to positive ones, because they can let trend inflation decrease the relative prices of their products without having to pay the menu cost for price adjustment. This leads to stronger short-run real effects, as well as to stronger long-run real effects through demand-supply interactions. However, for small and for very large monetary shocks, positive shocks have turned out to be more effective in the long run than negative ones, since micro-level price adjustment is empirically stronger downwards than upwards, if it happens.

The implications of my results for monetary policy are straightforward. If money is actually not neutral in the long run, then central banks should put more emphasis on following real economic targets besides following their primary target of maintaining a low and stable inflation rate. Under long-run monetary non-neutrality, restrictive monetary shocks aimed to reduce inflation lead to long-run real economic losses, which may not be compensated by the benefits of disinflation. I agree with Fontana and Palacio-Vera (2007) that in such a situation, central banks should follow a strategy similar to the one that they call the "flexible opportunist approach". They should not react to small inflationary shocks, they should wait for a deflationary shock instead to take the inflation rate back to the vicinity of its target value without any kind of monetary policy intervention. This way, central banks can avoid causing long-run damages to the real economy. Of course, if inflationary shocks are large, central banks should react to them by restrictive monetary policy measures. In case of small deflationary shocks, they should not wait for anything, since expansionary monetary policy measures may lead to long-run real economic benefits, and they help keeping the inflation rate around its target value at the same time. While designing their monetary policies, central banks should keep in my mind the two limitations that I have pointed out in the paper: the long-run real effect that they are able to exert on the economy decreases with the size of the monetary shock, and negative monetary shocks are more effective in the long run than positive ones in the intermediate range of the shock size.

The study presented in this paper can be considered as the first step of a more extended research program. More research has to be done in order to understand the nature of long-run monetary non-neutrality in more detail. First of all, the extent of the long-run real effects of monetary shocks depend crucially on parameter η, which determines the strength of demand-supply interactions. I have come up with a simple empirical estimate for its value, but a complete empirical paper should be devoted to producing a better founded econometric estimate for it. Second, demand-supply interactions are often considered to be stronger downwards than upwards. It would be interesting to come up with an empirical estimate for this asymmetry and to see how it affects the asymmetry between the long-run real effects of positive and negative monetary shocks. Third, some papers suggest that similar to price adjustment, demand-supply interactions may also be nonlinear and subject to threshold effects. Fixed costs of market entry (Dixit, 1989, 1992) or capital adjustment (Bassi – Lang, 2016) imply that potential growth will react nonlinearly to changes in the output gap.

Fourth, the presence of *macro-level* interactions between aggregate demand and aggregate supply is simply assumed in my model[47] without any kind of *microeconomic* foundation. If one would like to understand the microeconomic mechanisms underlying demand-supply interactions, one should develop an agent-based model of the whole macroeconomy, not just of the goods market. If one would like to include all the economic mechanisms in the macro model that possibly underlie demand-supply interactions, then the model should include an appropriate description of the process of innovation, of the labor market and of the process of capital accumulation. If one strives for a better understanding of the monetary transmission mechanism, through which the long-run real effects of monetary policy manifest themselves, then one should also include a financial intermediary sector and a credit market in the macro model. Fourth, the assumption of an optimizing representative household in the demand side of the goods market also prevents supporting the model with more detailed microeconomic foundations. It should be assumed in the macro model that the demand side of the goods market is populated by many boundedly rational, heterogeneous households, which interact with firms through an appropriately designed decentralized disequilibrium mechanism of market matching. This would allow me to exploit the possibilities in the agent-based nature of the model much better. The reason why I have assumed a simple market mechanism that assures equilibrium in the goods market in the long run is that it is not trivial, how long-run monetary non-neutrality should be defined in a model that does not converge to a long-run equilibrium, i.e. to a steady state after it has been hit by a monetary shock. Hence, maintaining the assumptions of a perfectly rational representative household and a simple equilibrium market mechanism has seemed to be reasonable in the first step of studying long-run monetary non-neutrality, but they will need to be relaxed in the further steps in order to understand the microeconomic foundations of long-run monetary non-neutrality more deeply.

To sum up, there is still a lot to do, but the simple agent-based menu cost model presented in this paper has still been able to provide us with a clue about where it is worth looking for, if we would like to understand the nature of long-run monetary non-neutrality. Returning to the motto of the paper, my results serve as another confirmation for Keynes that he has not been "wasting his time", when he was working on a monetary theory of production, in which money is not neutral either in the short run, or in the long run.

[47] However, the assumption is motivated by some economic mechanisms already know in the literature, as well as by some simple empirical estimations.

APPENDIX

Appendix A: The Variance of Idiosyncratic Productivity Shocks

In this appendix, I prove that conditional on arrival, the random draws $\tilde{\zeta}_{i,g,t}$ underlying idiosyncratic productivity shocks $\zeta_{i,g,t}$ have to be drawn from a probability distribution with variance

$$\sigma^2 = \frac{\sigma_\zeta^2}{\left[1+\frac{\chi(2+\chi)}{G}\right]\lambda}, \tag{A1}$$

if one would like to assure that the variance of idiosyncratic productivity shocks $\zeta_{i,g,t}$ is exactly equal to σ_ζ^2.

In the first step of the proof, I am going to prove that if the underlying random draws $\tilde{\zeta}_{i,g,t}$ are drawn from a probability distribution with variance σ^2 conditional on arrival, then the variance of the underlying random draws will be

$$Var(\tilde{\zeta}_{i,g,t}) = \lambda\sigma^2. \tag{A2}$$

Let X_1 and X_2 denote two random variables with probability density functions $f_1(x_1)$ and $f_2(x_2)$, respectively, where x_1 and x_2 are particular realizations of X_1 and X_2. If $f_2(x_2)$ is the probability distribution function of the normal distribution with mean 0 and variance σ^2, and $f_1(x_1)$ is defined as

$$f_1(x_1) = \begin{cases} 1 & \text{if } x_1 = 0 \\ 0 & \text{otherwise} \end{cases},$$

then random variable $\tilde{\zeta}_{i,g,t}$ is a mixture of random variables X_1 and X_2, which are weighted with the probabilities that a shock does not arrive $(1-\lambda)$ and that it arrives (λ), respectively. X_1 is actually a constant equal to 0.

The probability density function of $\tilde{\zeta}_{i,g,t}$ is the weighted sum of the probability density functions of X_1 and X_2, where the weights are $1-\lambda$ and λ:

$$f_{\tilde{\zeta}}(\tilde{\zeta}) = \begin{cases} (1-\lambda)\cdot 1 + \lambda\cdot f_2(\tilde{\zeta}) & \text{if } \tilde{\zeta} = 0 \\ (1-\lambda)\cdot 0 + \lambda\cdot f_2(\tilde{\zeta}) & \text{otherwise} \end{cases},$$

where $\tilde{\zeta}$ denotes a particular realization of $\tilde{\zeta}_{i,g,t}$. The probability density function can be simplified to

$$f_{\tilde{\zeta}}(\tilde{\zeta}) = \begin{cases} 1-\lambda+\lambda f_2(\tilde{\zeta}) & \text{if } \tilde{\zeta} = 0 \\ \lambda f_2(\tilde{\zeta}) & \text{otherwise} \end{cases}.$$

In order to compute the variance of $\tilde{\zeta}_{i,g,t}$, the first and the second moments of its probability distribution will have to be calculated. Let us start with the first moment, the expected value:

$$\mathbb{E}(\tilde{\zeta}_{i,g,t}) = \int_{-\infty}^{\infty} \tilde{\zeta} f_{\tilde{\zeta}}(\tilde{\zeta})d\tilde{\zeta} = \int_{-\infty}^{\infty} \tilde{\zeta}\lambda f_2(\tilde{\zeta})d\tilde{\zeta} - 0\cdot\lambda f_2(\tilde{\zeta}) +$$
$$+0\cdot\left[1-\lambda+\lambda f_2(\tilde{\zeta})\right] = \lambda\int_{-\infty}^{\infty} \tilde{\zeta} f_2(\tilde{\zeta})d\tilde{\zeta} = \lambda\cdot\mathbb{E}(X_2) = \lambda\cdot 0 = 0,$$

where I have made use of several properties of integrals, as well as the fact that $\int_{-\infty}^{\infty} \tilde{\zeta} f_2(\tilde{\zeta}) d\tilde{\zeta}$ is equal to the expected value of X_2. I have got to the result that the expected value of $\tilde{\zeta}_{i,g,t}$ is 0, just like the expected values of the two random variables, the mixture of which it is composed of.

Now, let us turn to calculating the second moment of the probability distribution of $\tilde{\zeta}_{i,g,t}$. It is equal to

$$\mathbb{E}(\tilde{\zeta}_{i,g,t}^2) = \int_{-\infty}^{\infty} \tilde{\zeta}^2 f_{\tilde{\zeta}}(\tilde{\zeta}) d\tilde{\zeta} = \int_{-\infty}^{\infty} \tilde{\zeta}^2 \lambda f_2(\tilde{\zeta}) d\tilde{\zeta} - 0^2 \cdot \lambda f_2(\tilde{\zeta}) +$$
$$+0^2 \cdot [1 - \lambda + \lambda f_2(\tilde{\zeta})] = \lambda \int_{-\infty}^{\infty} \tilde{\zeta}^2 f_2(\tilde{\zeta}) d\tilde{\zeta} = \lambda \cdot \mathbb{E}(X_2^2) =$$
$$= \lambda \cdot [Var(X_2) + \mathbb{E}^2(X_2)] = \lambda \cdot (\sigma^2 + 0^2) = \lambda\sigma^2,$$

where I have again made use of several properties of integrals, the fact that $\int_{-\infty}^{\infty} \tilde{\zeta}^2 f_2(\tilde{\zeta}) d\tilde{\zeta}$ is equal to the second moment of X_2, as well as the definition of the variance of X_2, according to which $Var(X_2) = \mathbb{E}(X_2^2) - \mathbb{E}^2(X_2)$.

A similar expression can be used to calculate the variance of $\tilde{\zeta}_{i,g,t}$:

$$Var(\tilde{\zeta}_{i,g,t}) = \mathbb{E}(\tilde{\zeta}_{i,g,t}^2) - \mathbb{E}^2(\tilde{\zeta}_{i,g,t}).$$

Substituting in the results for the first and the second moments of the probability distribution of $\tilde{\zeta}_{i,g,t}$, the variance of $\tilde{\zeta}_{i,g,t}$ becomes

$$Var(\tilde{\zeta}_{i,g,t}) = \lambda\sigma^2, \tag{A2}$$

which is exactly what I have wanted to prove in the first step.

Now, let us turn to the second step of the proof, during which I am going to use equation (A2) to prove that the random draws $\tilde{\zeta}_{i,g,t}$ underlying idiosyncratic productivity shocks $\zeta_{i,g,t}$ have to be drawn from a probability distribution with variance defined by equation (A1) in order to assure that the variance of idiosyncratic productivity shocks is equal to σ_ζ^2.

Let us calculate the variance of $\zeta_{i,g,t}$ assuming that the variance of $\tilde{\zeta}_{i,g,t}$ is given by equation (A2). Remember that the realizations of good-specific productivity shocks are determined by the underlying i.i.d. random draws $\tilde{\zeta}_{i,g,t}$ through equation (5):

$$\zeta_{i,g,t} = \tilde{\zeta}_{i,g,t} + \chi \text{mean}_g(\tilde{\zeta}_{i,g,t}). \tag{5}$$

Using equation (5), the variance of $\zeta_{i,g,t}$ can be written as

$$Var(\zeta_{i,g,t}) = Var\left(\tilde{\zeta}_{i,g,t} + \chi \frac{\sum_{g=1}^{G} \tilde{\zeta}_{i,g,t}}{G}\right).$$

Making use of the properties of the variance operator, $Var(\zeta_{i,g,t})$ can be manipulated to get

$$Var(\zeta_{i,g,t}) = Var(\tilde{\zeta}_{i,g,t}) + \frac{\chi^2}{G^2} Var\left(\sum_{g=1}^{G} \tilde{\zeta}_{i,g,t}\right) + 2Cov\left(\tilde{\zeta}_{i,g,t}, \frac{\chi}{G} \sum_{g=1}^{G} \tilde{\zeta}_{i,g,t}\right).$$

I have just proved that $Var(\tilde{\zeta}_{i,g,t}) = \lambda\sigma^2$, while in case of the second and the third terms, I can again use the properties of the variance and covariance operators to manipulate them further. In case of the second term, I make use of the assumption that the random draws $\tilde{\zeta}_{i,g,t}$ are independent of each other, as well. I get

$$Var(\zeta_{i,g,t}) = \lambda\sigma^2 + \frac{\chi^2}{G^2}\sum_{g=1}^{G} Var(\tilde{\zeta}_{i,g,t}) + 2 \cdot \frac{\chi}{G} \cdot \sum_{h=1}^{G} Cov\left(\tilde{\zeta}_{i,g,t}, \tilde{\zeta}_{i,h,t}\right).$$

The random draws $\tilde{\zeta}_{i,g,t}$ are identically distributed with the same variance, hence $\sum_{g=1}^{G} Var(\tilde{\zeta}_{i,g,t}) = G \cdot Var(\tilde{\zeta}_{i,g,t}) = G\lambda\sigma^2$. They are independent of each other, as well, i.e. $Cov(\tilde{\zeta}_{i,g,t}, \tilde{\zeta}_{i,h,t}) = 0$ for $\forall g \neq h$. Because of the latter assumption, it will be useful to divide the sum in the third term to the sum of two further terms:

$$Var(\zeta_{i,g,t}) = \lambda\sigma^2 + \frac{\chi^2}{G^2} \cdot G\lambda\sigma^2 + \frac{2\chi}{G}\left[\sum_{h \neq g} Cov(\tilde{\zeta}_{i,g,t}, \tilde{\zeta}_{i,h,t}) + Var(\tilde{\zeta}_{i,g,t})\right],$$

where I have made use of the fact that $Cov(\tilde{\zeta}_{i,g,t}, \tilde{\zeta}_{i,g,t}) = Var(\tilde{\zeta}_{i,g,t})$.

As $Cov(\tilde{\zeta}_{i,g,t}, \tilde{\zeta}_{i,h,t}) = 0$ for $\forall g \neq h$ because of the independency assumption, $\sum_{h \neq g} Cov(\tilde{\zeta}_{i,g,t}, \tilde{\zeta}_{i,h,t}) = 0$. It has also been proved that $Var(\tilde{\zeta}_{i,g,t}) = \lambda\sigma^2$, hence the expression for $Var(\zeta_{i,g,t})$ can be simplified to

$$Var(\zeta_{i,g,t}) = \lambda\sigma^2 + \frac{\chi^2}{G^2} \cdot G\lambda\sigma^2 + \frac{2\chi}{G} \cdot \lambda\sigma^2.$$

After some straightforward manipulations, it turns out that the variance of idiosyncratic productivity shocks is

$$Var(\zeta_{i,g,t}) = \left[1 + \frac{\chi(2+\chi)}{G}\right]\lambda\sigma^2.$$

Hence, if one would like to set the variance of idiosyncratic productivity shocks $\zeta_{i,g,t}$ equal to σ_ζ^2, then conditional on arrival, the random draws $\tilde{\zeta}_{i,g,t}$ underlying idiosyncratic productivity shocks $\zeta_{i,g,t}$ have to be drawn from a probability distribution with variance

$$\sigma^2 = \frac{\sigma_\zeta^2}{\left[1+\frac{\chi(2+\chi)}{G}\right]\lambda}. \tag{A1}$$

This is what I have wanted to prove.

Appendix B: The Within-Firm Correlation of Good-Specific Productivity Shocks

In this appendix, I prove that if one would like the within-firm correlation of good-specific productivity shocks to be equal to $\rho_\zeta \in [-1, 1)$, then the value of parameter χ has to be set according to equation (6), which I repeat here for convenience:

$$\chi = \frac{\sqrt{1+\rho_\zeta[(1-\rho_\zeta)G-(2-\rho_\zeta)]}}{1-\rho_\zeta} - 1. \tag{6}$$

The correlation between good-specific productivity shocks hitting goods g and h (where $g \neq h$) supplied by firm i in period t is

$$\rho_\zeta = \frac{Cov(\zeta_{i,g,t}, \zeta_{i,h,t})}{\sigma(\zeta_{i,g,t}) \cdot \sigma(\zeta_{i,h,t})}, \tag{B1}$$

where $\sigma(\zeta_{i,g,t})$ is the standard deviation of $\zeta_{i,g,t}$. As $\zeta_{i,g,t}$ and $\zeta_{i,h,t}$ are identically distributed, their standard deviations are the same. Hence, the denominator in equation (B1) has to be equal to the variance of $\zeta_{i,g,t}$:

$$\rho_\zeta = \frac{Cov(\zeta_{i,g,t}, \zeta_{i,h,t})}{Var(\zeta_{i,g,t})}. \tag{B2}$$

It is known by assumption that $Var(\zeta_{i,g,t}) = \sigma_\zeta^2$. Hence, only the covariance of good-specific productivity shocks needs to be calculated.

Remember that the realizations of good-specific productivity shocks are determined by the underlying i.i.d. random draws $\tilde{\zeta}_{i,g,t}$ through equation (5):

$$\zeta_{i,g,t} = \tilde{\zeta}_{i,g,t} + \chi \text{mean}_g(\tilde{\zeta}_{i,g,t}). \tag{5}$$

Using equation (5), the covariance between $\zeta_{i,g,t}$ and $\zeta_{i,h,t}$ can be written as

$$Cov(\zeta_{i,g,t}, \zeta_{i,h,t}) = Cov\left(\tilde{\zeta}_{i,g,t} + \chi \cdot \frac{\sum_{g=1}^{G} \tilde{\zeta}_{i,g,t}}{G}, \tilde{\zeta}_{i,h,t} + \chi \cdot \frac{\sum_{g=1}^{G} \tilde{\zeta}_{i,g,t}}{G}\right).$$

Making use of the properties of the covariance operator, this can be manipulated further as

$$Cov(\zeta_{i,g,t}, \zeta_{i,h,t}) = Cov(\tilde{\zeta}_{i,g,t}, \tilde{\zeta}_{i,h,t}) + Cov\left(\tilde{\zeta}_{i,g,t}, \frac{\chi}{G} \sum_{g=1}^{G} \tilde{\zeta}_{i,g,t}\right) +$$
$$+Cov\left(\frac{\chi}{G} \sum_{g=1}^{G} \tilde{\zeta}_{i,g,t}, \tilde{\zeta}_{i,h,t}\right) + Var\left(\frac{\chi}{G} \sum_{g=1}^{G} \tilde{\zeta}_{i,g,t}\right).$$

As $\tilde{\zeta}_{i,g,t}$ and $\tilde{\zeta}_{i,h,t}$ are independent, $Cov(\tilde{\zeta}_{i,g,t}, \tilde{\zeta}_{i,h,t}) = 0$. The remaining three terms can be manipulated further using the properties of the variance and covariance operators:

$$Cov(\zeta_{i,g,t}, \zeta_{i,h,t}) = \frac{\chi}{G} Cov\left(\tilde{\zeta}_{i,g,t}, \sum_{g=1}^{G} \tilde{\zeta}_{i,g,t}\right) +$$
$$+\frac{\chi}{G} Cov\left(\sum_{g=1}^{G} \tilde{\zeta}_{i,g,t}, \tilde{\zeta}_{i,h,t}\right) + \frac{\chi^2}{G^2} Var\left(\sum_{g=1}^{G} \tilde{\zeta}_{i,g,t}\right).$$

Again, making use of the properties of the covariance operator, including the fact that the covariances of $\tilde{\zeta}_{i,g,t}$ and $\tilde{\zeta}_{i,h,t}$ with themselves are equal to their variances, the above expression can be written as

$$Cov(\zeta_{i,g,t}, \zeta_{i,h,t}) = \frac{\chi}{G}\left[\sum_{h \neq g} Cov(\tilde{\zeta}_{i,g,t}, \tilde{\zeta}_{i,h,t}) + Var(\tilde{\zeta}_{i,g,t})\right] +$$

$$+\frac{\chi}{G}\left[\sum_{g\neq h} Cov\big(\tilde{\zeta}_{i,g,t},\tilde{\zeta}_{i,h,t}\big)+Var\big(\tilde{\zeta}_{i,h,t}\big)\right]+\frac{\chi^2}{G^2}Var\left(\sum_{g=1}^{G}\tilde{\zeta}_{i,g,t}\right).$$

As $\tilde{\zeta}_{i,g,t}$ and $\tilde{\zeta}_{i,h,t}$ are independent, $Cov\big(\tilde{\zeta}_{i,g,t},\tilde{\zeta}_{i,h,t}\big)=0$, if $g\neq h$. Hence, $\sum_{h\neq g} Cov\big(\tilde{\zeta}_{i,g,t},\tilde{\zeta}_{i,h,t}\big)$ and $\sum_{g\neq h} Cov\big(\tilde{\zeta}_{i,g,t},\tilde{\zeta}_{i,h,t}\big)$ are equal to 0, as well. It is also known that $Var\big(\sum_{g=1}^{G}\tilde{\zeta}_{i,g,t}\big)=\sum_{g=1}^{G}Var\big(\tilde{\zeta}_{i,g,t}\big)=G\cdot Var\big(\tilde{\zeta}_{i,g,t}\big)$, since the $\tilde{\zeta}_{i,g,t}$ random draws are independent of each other, and they are identically distributed with the same variances. Therefore, the covariance between $\zeta_{i,g,t}$ and $\zeta_{i,h,t}$ can be written as

$$Cov\big(\zeta_{i,g,t},\zeta_{i,h,t}\big)=\frac{2\chi}{G}Var\big(\tilde{\zeta}_{i,g,t}\big)+\frac{\chi^2}{G}Var\big(\tilde{\zeta}_{i,g,t}\big).$$

Following some straightforward manipulations, the expression for the covariance between $\zeta_{i,g,t}$ and $\zeta_{i,h,t}$ becomes

$$Cov\big(\zeta_{i,g,t},\zeta_{i,h,t}\big)=\frac{\chi(2+\chi)}{G}Var\big(\tilde{\zeta}_{i,g,t}\big).$$

I prove in *Appendix A* that the random draws underlying good-specific productivity shocks have to be drawn from a probability distribution with variance $Var\big(\tilde{\zeta}_{i,g,t}\big)=\sigma_\zeta^2/\big[1+\frac{\chi(2+\chi)}{G}\big]$ in order to assure that that the variance of good-specific productivity shocks is σ_ζ^2. Substituting this into the previous equation and carrying out some straightforward manipulations, the final expression for the covariance between $\zeta_{i,g,t}$ and $\zeta_{i,h,t}$ turns out to be

$$Cov\big(\zeta_{i,g,t},\zeta_{i,h,t}\big)=\frac{\chi(2+\chi)}{\chi(2+\chi)+G}\sigma_\zeta^2. \tag{B3}$$

Substituting equation (B3) together with the assumption that $Var\big(\zeta_{i,g,t}\big)=\sigma_\zeta^2$ into equation (B2), and simplifying the resulting expression, the within-firm correlation between good-specific productivity shocks $\zeta_{i,g,t}$ and $\zeta_{i,h,t}$ turns out to be

$$\rho_\zeta=\frac{\chi(2+\chi)}{\chi(2+\chi)+G}. \tag{B4}$$

In *Subsection 3.2*, I take the value of ρ_ζ as given, and set the value of χ so that the model produces a within-firm correlation between good-specific productivity shocks equal to ρ_ζ. To determine the value of χ that is consistent with a particular value of ρ_ζ, χ has to be expressed from equation (B4) as a function of ρ_ζ. This leads to the following quadratic equation for χ:

$$\big(1-\rho_\zeta\big)\chi^2+2\big(1-\rho_\zeta\big)\chi-\rho_\zeta G=0.$$

I have assumed that $\chi>0$, therefore I keep the positive solution of the equation only, according to which

$$\chi=\frac{\sqrt{1+\rho_\zeta\big[(1-\rho_\zeta)G-(2-\rho_\zeta)\big]}}{1-\rho_\zeta}-1. \tag{6}$$

Thus, I have proven that if one would like the within-firm correlation of good-specific productivity shocks to be equal to ρ_ζ, then the value of parameter χ does actually have to be set according to equation (6).

Appendix C: The Equivalence between the Growth Rate of Potential Output and the Growth Rate of the Aggregate Component of Supply Potentials

In this appendix, I prove that the growth rate of potential output is the same as the growth rate of the aggregate component of supply potentials in the agent-based menu cost model presented in *Section 3*. Hence, the growth rate of the aggregate component can be substituted with the growth rate of potential output, when estimating equation (4) using empirical data, provided that the law of large numbers holds for idiosyncratic productivity shocks in reality, just like in the model.

Let us start from the assumption, according to which the supply potential of good g produced by firm i in period t can be decomposed into two components as

$$\bar{q}_{i,g,t} = \mu_t \cdot \delta_{i,g,t}, \tag{C1}$$

where μ_t is the aggregate component of the supply potential, which is common to all product varieties supplied in the market, and $\delta_{i,g,t}$ is the good-specific component of the supply potential, which is independent across firms, but is correlated across the goods produced by the same firm, as well as in time.

Firm-level potential output $\bar{q}_{i,t}$ is computed as the CES aggregate of the supply potentials of the goods produced by firm i:

$$\bar{q}_{i,t} = \left(\sum_{g=1}^{G} \bar{q}_{i,g,t}^{\frac{\gamma-1}{\gamma}}\right)^{\frac{\gamma}{\gamma-1}}. \tag{C2}$$

Substituting equation (C1) into equation (C2) and carrying out some straightforward manipulations, it turns out that firm-level potential output can be expressed as

$$\bar{q}_{i,t} = \mu_t \cdot \delta_{i,t}, \tag{C3}$$

where $\delta_{i,t} = \left(\sum_{g=1}^{G} \delta_{i,g,t}^{\frac{\gamma-1}{\gamma}}\right)^{\frac{\gamma}{\gamma-1}}$ is the CES aggregate of the good-specific components of the supply potentials of the goods produced by firm i, and it can be interpreted as the firm-specific component of firm-level potential output. Note that the firm-specific components $\delta_{i,t}$ are independent across firms, since I have assumed that good-specific productivity shocks are correlated only across the goods produced by the same firm, and not across different firms.

Macro-level potential output is calculated as the CES aggregate of firm-level potential outputs:

$$\bar{Q}_t = \left(\sum_{i=1}^{N} \bar{q}_{i,t}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}. \tag{C4}$$

Substituting equation (C3) into equation (C4), the following expression can be obtained for potential output after some straightforward algebraic manipulations:

$$\bar{Q}_t = \delta \cdot \mu_t, \tag{C5}$$

where $\delta = \left(\sum_{i=1}^{N} \delta_{i,t}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}$ is the CES aggregate of the firm-specific components of firm-level potential output, and it can be considered to be constant in time, if the number of firms N is large enough, since the law of large numbers holds in the model for idiosyncratic productivity shocks. Firm-specific components $\delta_{i,t}$ are independent of each other, and they are identically distributed, hence their aggregate must converge to a constant number, as N tends to infinity, according to the law of large numbers. I set the number of firms to 1000 in model variants with single-product firms and to 500 in model variants with multiproduct firms. These numbers are large enough for the aggregate of firm-specific components to be considered as approximately equal to a constant.

The aggregate component of supply potentials can be expressed from equation (C5) as

$$\mu_t = \frac{\bar{Q}_t}{\delta}.$$

Taking the logarithm of both sides of the equation,

$$\log \mu_t = \log \bar{Q}_t - \log \delta.$$

Using this expression for $\log \mu_t$, the growth rate of the aggregate component of supply potentials can be written as

$$\log g_t^{\mu} = \log \frac{\mu_t}{\mu_{t-1}} = \log \mu_t - \log \mu_{t-1} = (\log \bar{Q}_t - \log \delta) - (\log \bar{Q}_{t-1} - \log \delta) =$$
$$= \log \bar{Q}_t - \log \delta - \log \bar{Q}_{t-1} + \log \delta = \log \bar{Q}_t - \log \bar{Q}_{t-1} = \Delta \log \bar{Q}_t.$$

Thus, it has turned out that

$$\log g_t^{\mu} = \Delta \log \bar{Q}_t,$$

and this is what I have wanted to prove: the growth rate of the aggregate component of supply potentials is indeed equal to the growth rate of potential output in my model. In reality, this is true only if the law of large numbers can be assumed to hold for idiosyncratic productivity shocks.

Appendix D: Solution of the Model Variant with Dynamically Optimizing Firms

In this appendix, I briefly describe the numerical method used for solving Model Variant C, the model variant with dynamically optimizing firms, and I characterize the policy function obtained as a result of the model solution.

I use value function iteration to solve the dynamic optimization problem of firms.[48] The steps of the solution are the following:

1. Before starting the iteration, I set the values of the parameters, I discretize AR(1) process (2) of nominal demand growth using a modified version of Tauchen (1986)'s method described by Adda and Cooper (2003), and I come up with initial guesses for the three value functions. The particular initial guesses do not affect the final solution. I choose the solution of the 1-period static optimization problem of the firm as the initial guess.

[48] A didactic description of the method of value function iteration can be found e.g. in Adda – Cooper (2003).

2. I compute the right-hand sides of Bellman equations (9) and (10) in each point of the two-dimensional grid of state variables taking the initial guesses for the value functions as given. This way, I get the updated values of changing and not changing the price for each grid point. Using these updated values, the updated value of the firm can also be computed in each grid point with the help of equation (11).
3. I define the discrepancy between the new and the old value function as the maximal absolute deviation of the updated and the initial values of the firm in the grid points. If this discrepancy is smaller than 0.0001, then the iteration stops, and the updated value functions become the solution to the system of Bellman equations.
4. Otherwise, the updated value functions take over the role of the initial guesses, and steps 2-3 are repeated until the discrepancy falls below 0.0001. The convergence of this iterative procedure is assured by the contraction mapping theorem.[49]
5. The value of the policy function of output in a given grid point is determined by picking the element of the control space that has maximized the value of the firm in that grid point.

Figure D.1: The Inaction Band in the State Space
Spanned by Nominal Demand Growth and Previous Period Output

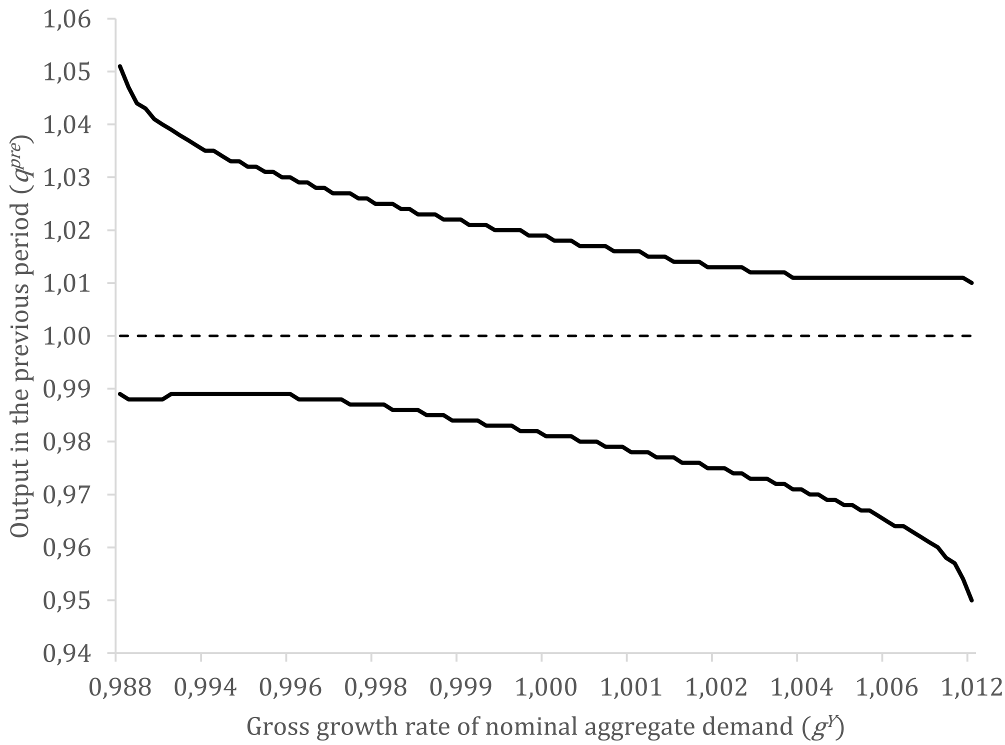


Figure D.1 provides one with an insight about the shape of the policy function. It shows the inaction band – the area between the two solid lines – in the two-dimensional state space. For combinations of nominal demand growth and previous period output that are inside the inaction band, firms decide to keep their prices unchanged. It can be seen that the inaction band is around the supply potential, which is equal to 1 under the chosen parameterization, but it is not symmetric. Intuitively, if firms produce near their supply

[49] The contraction mapping theorem and its proof can be found e.g. in Stokey – Lucas (1989).

potentials, they cannot gain much by changing the price, hence they are reluctant to pay the menu cost for price adjustment. But if nominal aggregate demand has decreased in the period, when the price decision is being made, then the inaction band moves up along the dimension of previous period output. The reason for this is that nominal demand growth is persistent: a large fall in the level of nominal aggregate demand is an indication for perfectly rational firms that it will probably decrease further in the following periods, hence their output will probably get closer to their supply potentials, if it has exceeded it in the previous period, even if they do not change their prices. Note that under such a large fall in nominal aggregate demand, it is optimal to increase a level of output not too much below the supply potential, and let the expected additional fall in nominal aggregate demand decrease it back to the vicinity of the supply potential.

Let us turn to the opposite end of the horizontal axis. If nominal aggregate demand has increased in the period, when the price decision is being made, then the inaction band moves down along the dimension of previous period output. This can be explained by the fact that a large rise in the level of nominal aggregate demand is an indication for firms that it will probably increase further in the near future, hence their output will probably approach their supply potentials, if it has been below it in the previous period, even if they do not pay the menu cost for price adjustment, and keep their prices unchanged. Under such a large rise in nominal aggregate demand, it is optimal to decrease a level of output not too much above the supply potential, and let the expected additional rise in nominal aggregate demand increase it back to a level near the supply potential.

REFERENCES

1. Ábrahám Árpád – White, Kirk (2006): The Dynamics of Plant-Level Productivity in U.S. Manufacturing. CES Working Paper, No. 06-20.
2. Acemoglu, Daron – Carvalho, Vasco M. – Ozdaglar, Asuman – Tahbaz-Salehi, Alireza (2012): The Network Origins of Aggregate Fluctuations. Econometrica, Vol. 80. No. 5. pp. 1977-2016.
3. Adda, Jerome – Cooper, Russell (2003): Dynamic Economics: Quantitative Methods and Applications. Cambridge – London: The MIT Press.
4. Akerlof, George A. – Yellen, Janet L. (1985): A Near-Rational Model of the Business Cycle with Wage and Price Inertia. The Quarterly Journal of Economics, Vol. 100. (Supplement) pp. 823-838.
5. Alvarez, Fernando – Le Bihan, Hervé – Lippi, Francesco (2016): The Real Effects of Monetary Shocks in Sticky Price Models: A Sufficient Statistic Approach. The American Economic Review, Vol. 106. No. 10. pp. 2817-2851.
6. Amable, Bruno – Henry, Jerome – Lordon, Frédéric – Topol, Richard (1993): Unit Root in the Wage-Price Spiral Is Not Hysteresis in Unemployment. Journal of Economic Studies, Vol. 20. No. 1-2. pp. 123-135.
7. Amable, Bruno – Henry, Jerome – Lordon, Frédéric – Topol, Richard (1994): Strong Hysteresis versus Zero Root Dynamics. Economic Letters, Vol. 44. No. 1-2. pp. 43-47.
8. Arestis, Philip – Sawyer, Malcolm (2009): Path Dependency and Demand-Supply Interactions in Macroeconomic Analysis. In: Arestis, Philip – Sawyer, Malcolm (eds.): Path Dependency and Macroeconomics. London: Palgrave Macmillan, pp. 1-36.
9. Assenza, Tiziana – Delli Gatti, Domenico – Grazzini, Jakob (2015): Emergent Dynamics of a Macroeconomic Agent Based Model with Capital and Credit. Journal of Economic Dynamics & Control, Vol. 50. pp. 5-28.
10. Atesoglu, H. Sonmez (2001): Long-Run Monetary Facts of the United States. Journal of Post Keynesian Economics, Vol. 23. No. 3. pp. 441-448.
11. Atesoglu, H. Sonmez – Emerson, Jamie (2009): Long-Run Monetary Neutrality. Applied Economics, Vol. 41. No. 16. pp. 2025-2036.
12. Babutsidze, Zakaria (2012): Asymmetric (S,s) Pricing: Implications for Monetary Policy. In: Gaffard, Jean-Luc – Napoletano, Mauro (eds.): Agent-Based Models and Economic Policy. Paris: Revue de l'OFCE, pp. 177-204.
13. Bachmann, Rüdiger – Bayer, Christian (2013): 'Wait-and-See' Business Cycles? Journal of Monetary Economics, Vol. 60. No. 6. pp. 704-719.
14. Baldiwn, Richard – Krugman, Paul R. (1989): Persistent Trade Effects of Large Exchange Rate Shocks. The Quarterly Journal of Economics, Vol. 104. No. 4. pp. 635-654.
15. Ball, Laurence M. (1999): Aggregate Demand and Long-Run Unemployment. Brookings Papers on Economic Activity, Vol. 1999. No. 2. pp. 189-251.
16. Ball, Laurence M. (2009): Hysteresis in Unemployment: Old and New Evidence. NBER Working Paper, No. 14818.
17. Ball, Laurence M. – Mankiw, N. Gregory (1994): Asymmetric Price Adjustment and Economic Fluctuations. The Economic Journal, Vol. 104. No. 423. pp. 247-261.

18. Barro, Robert J. (1972): A Theory of Monopolistic Price Adjustment. The Review of Economic Studies, Vol. 39. No. 1. pp. 17-26.
19. Bassi, Federico – Lang, Dany (2016): Investment Hysteresis and Potential Output: A Post-Keynesian-Kaleckian-Agent-Based Approach. Economic Modelling, Vol. 52. Part A pp. 35-49.
20. Bergoeing, Raphael – Hernando, Andrés – Repetto, Andrea (2003): Idiosyncratic Productivity Shocks and Plant-Level Heterogeneity. Documentos de Trabajo, No. 173., Universidad de Chile, Centro de Economía Aplicada.
21. Bils, Mark – Klenow, Peter J. (2004): Some Evidence on the Importance of Sticky Prices. Journal of Political Economy, Vol. 112. No. 5. pp. 947-985.
22. Blanchard, Olivier J. – Kiyotaki, Nobuhiro (1987): Monopolistic Competition and the Effects of Aggregate Demand. The American Economic Review, Vol. 77. No. 4. pp. 647-666.
23. Blanchard, Olivier J. – Summers, Lawrence H. (1986): Hysteresis and the European Unemployment Problem. NBER Macroeconomics Annual, Vol. 1. pp. 15-78.
24. Blanchard, Olivier J. – Summers, Lawrence H. (1987): Hysteresis in Unemployment. European Economic Review, Vol. 31. No. 1-2. pp. 288-295.
25. Boschen, John F. – Mills, Leonard O. (1995): Tests of Long-Run Neutrality Using Permanent Monetary and Real Shocks. Journal of Monetary Economics, Vol. 35. No. 1. pp. 25-44.
26. Boschen, John F. – Otrok, Christopher M. (1994): Long-Run Neutrality and Superneutrality in an ARIMA Framework: Comment. The American Economic Review, Vol. 84. No. 5. pp. 1470-1473.
27. Bullard, James (1999): Testing Long-Run Monetary Neutrality Propositions: Lessons from the Recent Research. Federal Reserve Bank of St. Louis Review, November/December 1999., pp. 57-77.
28. Calvo, Guillermo A. (1983): Staggered Prices in a Utility-Maximizing Framework. Journal of Monetary Economics, Vol. 12. No. 3. pp. 383-398.
29. Camerer, Colin F. – Loewenstein, George – Rabin, Matthew (2004): Advances in Behavioral Economics. Princeton – Oxford: Princeton University Press.
30. Caplin, Andrew S. – Spulber, Daniel F. (1987): Menu Costs and the Neutrality of Money. The Quarterly Journal of Economics, Vol. 102. No. 4. pp. 703-725.
31. Castro, Rui – Clementi, Gian Luca – Lee, Yoonsoo (2015): Cross Sectoral Variation in the Volatility of Plant Level Idiosyncratic Shocks. The Journal of Industrial Economics, Vol. 63. No. 1. pp. 1-29.
32. Chen, Haipeng (Allan) – Levy, Daniel – Ray, Sourav – Bergen, Mark (2008): Asymmetric Price Adjustment in the Small. Journal of Monetary Economics, Vol. 55. No. 4. pp. 728-737.
33. Coe, Patrick J. – Nason, James M. (1999): Long-Run Monetary Neutrality in Three Samples: The United Kingdom, the United States, and the Small. Working Papers, 1999-06., University of Calgary, Department of Economics.
34. Costain, James – Nakov, Anton (2011): Distributional Dynamics under Smoothly State-Dependent Pricing. Journal of Monetary Economics, Vol. 58. No. 6-8. pp. 646-665.
35. Cottrell, Allin (1994): Post-Keynesian Monetary Economics. Cambridge Journal of Economics, Vol. 18. No. 6. pp. 587-605.

36. Cover, James P. (1992): Asymmetric Effects of Positive and Negative Money-Supply Shocks. The Quarterly Journal of Economics, Vol. 107. No. 4. pp. 1261-1282.
37. Cross, Rod B. (1987): Hysteresis and Instability in the Natural Rate of Unemployment. The Scandinavian Journal of Economics, Vol. 89. No. 1. pp. 71-89.
38. Cross, Rod B. (1993): On the Foundations of Hysteresis in Economic Systems. Economics and Philosophy, Vol. 9. No. 1. pp. 53-74.
39. Davidson, Paul (1987): Sensible Expectations and the Long-Run Non-Neutrality of Money. Journal of Post Keynesian Economics, Vol. 10. No. 1. pp. 146-153.
40. Dawid, Herbert – Gemkow, Simon – Harting, Philipp – van der Hoog, Sander – Neugart, Michael (2012): The Eurace@Unibi Model: An Agent-Based Macroeconomic Model for Economic Policy Analysis. Working Paper, Universität Bielefeld.
41. De Grauwe, Paul – Costa Storti, Cláudia (2004): The Effects of Monetary Policy: A Meta-Analysis. CESifo Working Paper, No. 1224.
42. De Long, J. Bradford – Summers, Lawrence H. (1988): How Does Macroeconomic Policy Affect Output? Brookings Papers on Economic Activity, Vol. 1988. No. 2. pp. 433-480.
43. Delgado, Francisco A. (1991): Hysteresis, Menu Costs, and Pricing with Random Exchange Rates. Journal of Monetary Economics, Vol. 28. No. 3. pp. 461-484.
44. Delli Gatti, Domenico – Desiderio, Saul – Gaffeo, Edoardo – Cirillo, Pasquale – Gallegati, Mauro (2011): Macroeconomics from the Bottom-Up. Milano: Springer-Verlag Italia.
45. Delli Gatti, Domenico – Gaffeo, Edoardo – Gallegati, Mauro – Palestrini, Antonio (2005): The Apprentice Wizard: Monetary Policy, Complexity and Learning. New Mathematics and Natural Computation, Vol. 1. No. 1. pp. 109-128.
46. Dixit, Avinash K. (1989): Hysteresis, Import Penetration, and Exchange Rate Pass-Through. The Quarterly Journal of Economics, Vol. 104. No. 2. pp. 205-228.
47. Dixit, Avinash K. (1991): Analytical Approximations in Models of Hysteresis. The Review of Economic Studies, Vol. 68. No. 1. pp. 141-151.
48. Dixit, Avinash K. (1992): Investment and Hysteresis. The Journal of Economic Perspectives, Vol. 6. No. 1. pp. 107-132.
49. Dixit, Avinash K. – Stiglitz, Joseph E. (1977): Monopolistic Competition and Optimum Product Diversity. The American Economic Review, Vol. 67. No. 3. pp. 297-308.
50. Dosi, Giovanni (2012): Economic Coordination and Dynamics: Some Elements of an Alternative „Evolutionary" Paradigm. LEM Working Paper Series, No. 2012/08.
51. Dosi, Giovanni – Fagiolo, Giorgio – Roventini, Andrea (2010): Schumpeter Meeting Keynes: A Policy-Friendly Model of Endogenous Growth and Business Cycles. Journal of Economic Dynamics & Control, Vol. 34. pp. 1748-1767.
52. Dosi, Giovanni – Fagiolo, Giorgio – Napoletano, Mauro – Roventini, Andrea – Treibich, Tania (2015): Fiscal and Monetary Policies in Complex Evolving Economies. Journal of Economic Dynamics & Control, Vol. 52. pp. 166-189.
53. Dosi, Giovanni – Napoletano, Mauro – Roventini, Andrea – Stiglitz, Joseph E. – Treibich, Tania (2017): Rational Heuristics? Expectations and Behaviors in Evolving Economies with Heterogeneous Interacting Agents. LEM Working Paper Series, No. 2017/31.

54. Duménil, Gérard – Lévy, Dominique (1991): Micro Adjustment toward Long-Term Equilibrium. Journal of Economic Theory, Vol. 53. No. 2. pp. 369-395.
55. Durlauf, Steven N. (1993): Nonergodic Economic Growth. The Review of Economic Studies, Vol. 60. No. 2. pp. 349-366.
56. Dutt, Amitava K. (2006): Aggregate Demand, Aggregate Supply and Economic Growth. International Review of Applied Economics, Vol. 20. No. 3. pp. 319-336.
57. Enders, Walter (2015): Applied Econometric Time Series. Wiley.
58. Fagiolo, Giorgio – Roventini, Andrea (2017): Macroeconomic Policy in DSGE and Agent-Based Models Redux: New Developments and Challenges Ahead. Journal of Artificial Societies and Social Simulation, Vol. 20. No. 1.
59. Fisher, Mark E. – Seater, John J. (1993): Long-Run Neutrality and Superneutrality in an ARIMA Framework. The American Economic Review, Vol. 83. No. 3. pp. 402-415.
60. Florio, Anna (2004): The Asymmetric Effects of Monetary Policy. Journal of Economic Surveys, Vol. 18. No. 3. pp. 409-426.
61. Fontana, Giuseppe (2007): Why Money Matters: Wicksell, Keynes and the New Consensus View on Monetary Policy. Journal of Post Keynesian Economics, Vol. 30. No. 1. pp. 43-60.
62. Fontana, Giuseppe – Palacio-Vera, Alfonso (2007): Are Long-Run Price Stability and Short-Run Output Stabilization All that Monetary Policy Can Aim for? Metroeconomica, Vol. 58. No. 2. pp. 269-298.
63. Gabaix, Xavier (2011): The Granular Origins of Aggregate Fluctuations. Econometrica, Vol. 79. No. 3. pp. 733-772.
64. Gaffeo, Edoardo – Gallegati, Mauro – Gostoli, Umberto (2015): An Agent-Based „Proof of Principle" for Walrasian Macroeconomic Theory. Computational and Mathematical Organization Theory, Vol. 21. No. 2. pp. 150-183.
65. Galí, Jordi (2008): Monetary Policy, Inflation and the Business Cycle: An Introduction to the New Keynesian Framework. Princeton: Princeton University Press.
66. Galí, Jordi (2015): Hysteresis and the European Unemployment Problem Revisited. NBER Working Paper, No. 21430.
67. Gertler, Mark – Leahy, John (2008): A Phillips Curve with an Ss Foundation. Journal of Political Economy, Vol. 116. No. 3. pp. 533-572.
68. Gigerenzer, Gerd (2008): Rationality for Mortals: How People Cope with Uncertainty. Oxford: Oxford University Press.
69. Gigerenzer, Gerd – Brighton, Henry (2009): Homo Heuristicus: Why Biased Minds Make Better Inferences. Topics in Cognitive Science, Vol. 1. No. 1. pp. 107-143.
70. Göcke, Matthias (2002): Various Concepts of Hysteresis Applied in Economics. Journal of Economic Surveys, Vol. 16. No. 2. pp. 167-188.
71. Golosov, Mikhail – Lucas, Robert E. (2007): Menu Costs and Phillips Curves. Journal of Political Economy, Vol. 115. No. 2. pp. 171-199.
72. Grazzini, Jakob – Richiardi, Matteo (2015): Estimation of Ergodic Agent-Based Models by Simulated Minimum Distance. Journal of Economic Dynamics & Control, Vol. 51. pp. 148-165.
73. Greenslade, Jennifer V. – Parker, Miles (2012): New Insights into Price-Setting Behaviour in the UK: Introduction and Survey Results. The Economic Journal, Vol. 122. No. 558. pp. F1-F15.

74. Guerini, Mattia – Napoletano, Mauro – Roventini, Andrea (2018): No Man Is and Island: The Impact of Heterogeneity and Local Interactions on Macroeconomic Dynamics. Economic Modelling, Vol. 68. pp. 82-95.
75. Haug, Alfred A. – Lucas, Robert F. (1997): Long-Run Neutrality and Superneutrality in an ARIMA Framework: Comment. The American Economic Review, Vol. 87. No. 4. pp. 756-759.
76. Hayek, Friedrich A. (1945): The Use of Knowledge in Society. The American Economic Review, Vol. 35. No. 4. pp. 519-530.
77. Hommes, Cars (2013): Behavioral Rationality and Heterogeneous Expectations in Complex Economic Systems. New York: Cambridge University Press.
78. Johansen, Søren. (1991): Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models. Econometrica, Vol. 59. No. 6. pp. 1551-1580.
79. Jovanovic, Boyan (1987): Micro Shocks and Aggregate Risk. The Quarterly Journal of Economics, Vol. 102. No. 2. pp. 395-409.
80. Kaldor, Nicholas (1957): A Model of Economic Growth. The Economic Journal, Vol. 67. No. 268. pp. 591-624.
81. Karádi Péter – Reiff Ádám (2012): Large Shocks in Menu Cost Models. ECB Working Paper, No. 1453.
82. Karádi Péter – Reiff Ádám (2019): Menu Costs, Aggregate Fluctuations, and Large Shocks. American Economic Journal: Macroeconomics. Vol. 11. No. 3. pp. 111-146.
83. Kehoe, Patrick J. – Midrigan, Virgiliu (2008): Temporary Price Changes and the Real Effects of Monetary Policy. NBER Working Paper, No. 14392.
84. Keynes, John M. (1921): A Treatise on Probability. London: MacMillan and Co.
85. King, Robert G. – Watson, Mark W. (1997): Testing Long-Run Neutrality. Federal Reserve Bank of Richmond Economic Quarterly, Vol. 83. No. 3. pp. 69-101.
86. Klenow, Peter J. – Kryvtsov, Oleksiy (2008): State-Dependent or Time-Dependent Pricing: Does It Matter for Recent U.S. Inflation? The Quarterly Journal of Economics, Vol. 123. No. 3. pp. 863-904.
87. Knight, Frank H. (1921): Risk, Uncertainty and Profit. Boston: Hart, Schaffner and Marx-Houghton Mifflin Co.
88. Koop, Gary – Pesaran, M. Hashem – Potter, Simon M. (1996): Impulse Response Analysis in Nonlinear Multivariate Models. Journal of Econometrics, Vol. 74. No. 1. pp. 119-147.
89. Kornai János – Martos Béla (1973): Autonomous Control of the Economic System. Econometrica, Vol. 41. No. 3. pp. 509-528.
90. Kriesler, Peter – Lavoie, Marc (2007): The New Consensus on Monetary Policy and its Post-Keynesian Critique. Review of Political Economy, Vol. 19. No. 3. pp. 387-404.
91. Lavoie, Marc (2006): A Post-Keynesian Amendment to the New Consensus on Monetary Policy. Metroeconomica, Vol. 57. No. 2. pp. 165-192.
92. Lavoie, Marc (2014): Post-Keynesian Economics: New Foundations. Cheltenham – Northampton: Edward Elgar.
93. Leijonhufvud, Axel (2006): Agent-Based Macro. In: Tesfatsion, Leigh – Judd, Kenneth L. (eds.): Handbook of Computational Economics, Volume 2: Agent-Based

Computational Economics. Amsterdam: North-Holland, Handbooks in Economics Series, pp. 1625-1637.

94. Lengnick, Matthias (2013): Agent-Based Macroeconomics: A Baseline Model. Journal of Economic Behavior & Organization, Vol. 86. pp. 102-120.
95. Lucas, Robert E. (1996): Nobel Lecture: Monetary Neutrality. Journal of Political Economy, Vol. 104. No. 4. pp. 661-682.
96. Mankiw, N. Gregory (1985): Small Menu Costs and Large Business Cycles: A Macroeconomic Model of Monopoly. The Quarterly Journal of Economics, Vol. 100. No. 2. pp. 529-538.
97. Midrigan, Virgiliu (2011): Menu Costs, Multiproduct Firms, and Aggregate Fluctuations. Econometrica, Vol. 79. No. 4. pp. 1139-1180.
98. Morgan, Donald P. (1993): Asymmetric Effects of Monetary Policy. Federal Reserve Bank of Kansas City Economic Review, Vol. 78. No. 2. pp. 21-33.
99. Müller, Georg – Ray, Sourav (2007): Asymmetric Price Adjustment: Evidence from Weekly Product-Level Scanner Price Data. Managerial and Decision Economics, Vol. 28. No. 7. pp. 723-736.
100. Nakamura, Emi – Steinsson, Jón (2008): Five Facts About Prices: A Reevaluation of Menu Cost Models. The Quarterly Journal of Economics, Vol. 123. No. 4. pp. 1415-1464.
101. Nakamura, Emi – Steinsson, Jón (2010): Monetary Non-Neutrality in a Multisector Menu Cost Model. The Quarterly Journal of Economics, Vol. 125. No. 3. pp. 961-1013.
102. O'Donnell, Rob (2013): Two Post-Keynesian Approaches to Uncertainty and Irreducible Uncertainty. In: Harcourt, G.C. – Kriesler, Peter (eds.): The Oxford Handbook of Post-Keynesian Economics, Volume 2: Critiques and Methodology. New York: Oxford University Press, pp. 124-142.
103. Olekalns, Nilss (1996): Some Further Evidence on the Long-Run Neutrality of Money. Economic Letters, Vol. 50. No. 3. pp. 393-398.
104. Orphanides, Athanasios – Solow, Robert M. (1990): Money, Inflation and Growth. In: Friedman, Benjamin M. – Hahn, Frank H. (eds.): Handbook of Monetary Economics, Volume 1. Amsterdam: North-Holland, Handbooks in Economics Series, pp. 223-261.
105. Phelps, Edmund S. (1972): Inflation Policy and Unemployment Theory. London: Macmillan.
106. Setterfield, Mark (2002): A Model of Kaldorian Traverse: Cumulative Causation, Structural Change and Evolutionary Hysteresis. In: Setterfield, Mark (ed.): The Economics of Demand-Led Growth: Challenging the Supply-Side Vision of the Long Run. Cheltenham – Northampton: Edward Elgar, pp. 215-233.
107. Setterfield, Mark (2009): Path Dependency, Hysteresis and Macrodynamics. In: Arestis, Philip – Sawyer, Malcolm (eds.): Path Dependency and Macroeconomics. London: Palgrave Macmillan, pp. 37-79.
108. Setterfield, Mark – Gouri Suresh, Shyam (2016): Multi-Agent Systems as a Tool for Analyzing Path-Dependent Macrodynamics. Structural Change and Economic Dynamics, Vol. 38. pp. 25-37.
109. Sheshinski, Eytan – Weiss, Yoram (1977): Inflation and Costs of Price Adjustment. The Review of Economic Studies, Vol. 44. No. 2. pp. 287-303.

110. Simon, Herbert A. (1972): Theories of Bounded Rationality. In: McGuire, C.B. – Radner, Roy (eds.): Decision and Organization: A Volume in Honor of Jacob Marschak. Amsterdam: North-Holland, pp. 161-176.
111. Stockey, Nancy L. – Lucas, Robert E. (1989): Recursive Methods in Economic Dynamics. Cambridge – London: Harvard University Press.
112. Stockhammer, Engelbert – Sturn, Simon (2012): The Impact of Monetary Policy on Unemployment Hysteresis. Applied Economics, Vol. 44. No. 21. pp. 2743-2756.
113. Storm, Servaas – Naastepad, C.W.M. (2012): Macroeconomics Beyond the NAIRU. Cambridge: Harvard University Press.
114. Tauchen, George (1986): Finite State Markov-Chain Approximations to Univariate and Vector Autoregressions. Economic Letters, Vol. 20. No. 2. pp. 177-181.
115. Tesfatsion, Leigh (2006): Agent-Based Computational Economics: A Constructive Approach to Economic Theory. In: Tesfatsion, Leigh – Judd, Kenneth L. (eds.): Handbook of Computational Economics, Volume 2: Agent-Based Computational Economics. Amsterdam: North-Holland, Handbooks in Economics Series, pp. 831-880.
116. Tversky, Amos – Kahneman, Daniel (1974): Judgement under Uncertainty: Heuristics and Biases. Science, Vol. 185. No. 4157. pp. 1124-1131.
117. Verdoorn, Petrus J. (1949): Fattori che regolano lo sviluppo della produttivitá del lavoro. L'Industria.
118. Weber, Axel A. (1994): Testing Long-Run Neutrality: Empirical Evidence for G7-Countries with Special Emphasis on Germany. Carnegie-Rochester Conference Series on Public Policy, Vol. 41. pp. 67-117.
119. Woodford, Michael (2003): Interest and Prices: Foundations of a Theory of Monetary Policy. Princeton: Princeton University Press.