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The long-run real effects of monetary shocks: Lessons from a hybrid post-Keynesian-DSGE-agent-based menu cost model

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ABSTRACT

This paper studies the long-run effects of monetary policy on real economic activity. It presents a hybrid menu cost model, the structure of which mimics that of dynamic stochastic general equilibrium models with fixed price adjustment costs (menu costs). It contains two mechanisms capable of generating long-run real effects in response to monetary shocks according to post-Keynesian macroeconomists, and its behavior is studied via agent-based simulations. After being calibrated to reproduce key features of the microdata, the model estimates that a typical monetary shock has substantial long-run real effects, with around one-quarter of the shock being absorbed by real output. However, the long-run effectiveness of a monetary shock turns out to decrease with its size. The key mechanisms generating long-run real effects are shown to be demand–supply interactions, that is, positive feedbacks from aggregate demand to aggregate supply. The results suggest that central banks should stronger emphasize stabilizing real economic activity when designing their monetary policies.

1. Introduction

Long-run monetary neutrality (LRMN) is a cornerstone of mainstream monetary macroeconomics. Money is said to be neutral in the long run if a permanent unanticipated shock to the level of the money supply does not permanently affect real economic activity (Lucas, 1996; Bullard, 1999).[1] Robert Lucas summarized the conventional wisdom about LRMN in his Nobel Lecture as follows: "… [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 important implications for the practice of monetary policy. If it holds, all the effects that central banks may exert on real economic activity are realized in the *short run*. In the long run, the price level will absorb all changes induced by the central bank in nominal aggregate demand. Although monetary policy may be effective in the short run because of price and wage rigidity, central banks should focus on maintaining low and stable inflation rates and smoothing short-run cyclical fluctuations, as they cannot influence real economic activity in the long run. Thus, LRMN is a core pre-assumption behind the optimality of the policy of strict inflation targeting suggested to central banks by early New Keynesian monetary theories (Woodford, 2003; Galí, 2008).

Despite its widespread acceptance, the empirical evidence regarding LRMN is far from unambiguous.[2] Several empirical studies, based on post-war data from the United States (U.S.), confirm that LRMN holds (Boschen and Otrok, 1994; Boschen and Mills, 1995; King and Watson, 1997). However, it is rejected to hold if the sample contains the Great Depression (Fisher and Seater, 1993). The decision to accept or reject the LRMN hypothesis is sensitive to the country considered (Olekalns, 1996; Haug and Lucas, 1997), the monetary aggregate used to measure the money supply (Weber, 1994; Coe and Nason, 1999), and the number and location of structural breaks allowed in the long-run trends of real output, and the money supply (Noriega et al., 2008; Ventosa-Santaulària and Noriega, 2015). Atesoglu (2001) and Atesoglu and Emerson (2009)

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[1] This paper does not deal with the issue of long-run monetary *superneutrality*, that is, the question of whether permanent unanticipated shocks to the *growth rate* of money supply affect the level of real economic activity in the long run. See Orphanides and Solow (1990) for a comprehensive survey about the theoretical literature of long-run monetary superneutrality.

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

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found evidence against LRMN even in post-war samples from the U.S. De Grauwe and Costa Storti (2004) argued that the reason why monetary policy has no long-run real effects according to many structural vector autoregression (SVAR) studies is that LRMN is often used as an assumption to identify exogenous monetary policy shocks. When applying different identifying assumptions, monetary policy usually turns out to have long-run real effects. In a recent empirical study, Jorda et al. (2020) identified exogenous monetary policy shocks using instrumental variable methods and applied a local projection method to estimate the long-run effects of these shocks on real output, which turned out to be significant.

If the empirical evidence against LRMN is taken seriously, the need arises to establish the magnitude of the real effects that monetary policy may exert on real economic activity in the long run and identify the key channels through which these effects may be realized. This paper takes steps to fill these gaps by proposing an estimate for the magnitude of the macro-level real effects that may emerge in the long run due to heterogeneous micro-level price adjustment to monetary shocks coupled with two economic mechanisms believed to generate long-run monetary non-neutrality (LRMNN) by post-Keynesian economists. These two mechanisms are nonlinear price adjustment and demand–supply interactions. The former term is used to refer to a micro-level pricing behavior that does not react to small demand and supply shocks, while the latter is modeled as a macro-level positive feedback from aggregate demand to aggregate supply (Palacio-Vera, 2005; Fontana, 2007; Fontana and Palacio-Vera, 2007; Kriesler and Lavoie, 2007). The paper clarifies the roles played by these mechanisms in the emergence of LRMNN. It studies the long-run real effects of monetary shocks with a hybrid post-Keynesian-DSGE-agent-based menu cost model. This model combines insights from dynamic stochastic general equilibrium (DSGE) models containing fixed price adjustment costs (menu costs) with ideas from post-Keynesian monetary macroeconomics, and its behavior is analyzed via agent-based simulations.

The model tries to "bridge the gap" between post-Keynesian, DSGE, and agent-based models, following the spirit of Dilaver et al. (2018), Gobbi and Grazzini (2019), and Haldane and Turrell (2019) who argue that there is a need for more hybrid models containing some agent-based features, while being directly comparable to the DSGE benchmark. The model presented in this paper fits into this hybrid modeling approach and extends it toward post-Keynesian macro models. Its structure mimics that of DSGE-type menu cost models developed for studying the *short-run* real effects of monetary shocks (Golosov and Lucas, 2007; Gertler and Leahy, 2008; Nakamura and Steinsson, 2010; Midrigan, 2011; Alvarez et al., 2016; Karádi and Reiff, 2019). It contains some post-Keynesian and agent-based features to make it suitable for analyzing the connections between heterogeneous micro-level price dynamics and the macro-level long-run real effects of monetary shocks. By turning the post-Keynesian and the agent-based features of the model on and off, their implications can be made clear regarding the long-run real effects of monetary shocks. Such a modeling approach facilitates comparison between post-Keynesian, DSGE, and agent-based models, while helping to clarify the economic mechanisms behind their different conclusions.

The model is calibrated to match the most important moments of two empirical distributions related to micro-level price adjustment, derived from one of the most popular empirical samples used for calibrating menu cost models, the Dominick's dataset (Midrigan, 2011; Alvarez et al., 2016). It estimates that a typical monetary shock has substantial long-run real effects, with around one-quarter of the shock absorbed by real aggregate output in the long run. The key post-Keynesian mechanism responsible for generating LRMNN is shown to be demand–supply interactions present in the economy. The other post-Keynesian mechanism, nonlinear price adjustment cannot explain LRMNN in an empirically relevant way within the context of the model. Still, it plays an important role in determining the magnitude of the long-run real effects of monetary shocks once they are brought to life by demand–supply interactions. The substantial long-run real effects do not imply that central banks can stimulate real economic activity in the long run without any limitations; the long-run effectiveness of a monetary shock is shown to decrease with its size, implying nonlinearly increasing inflationary effects in the long run as a function of the shock size. The long-run real effects of monetary shocks are asymmetric in the model as prices are assumed to react differently to positive and negative shocks, in line with the empirical evidence. There is an intermediate range of the shock size, within which negative monetary shocks are more effective in the long run, but positive shocks are more effective outside of this range.

The results have important implications for the conduct of monetary policy. If the long-run real effects of monetary shocks are substantial, there is no *divine coincidence* (Blanchard and Galí, 2007); central banks do not simultaneously stabilize real economic activity by stabilizing the inflation rate. Short-run disinflations cause long-run damages to the real economy that their benefits might not compensate. Under such circumstances, strict inflation targeting cannot be the optimal monetary policy. In addition to following their primary target of maintaining price stability, central banks should emphasize stabilizing the real economy even stronger than in the presence of a simple short-run policy trade-off. Two post-Keynesian authors, Fontana and Palacio-Vera (2007), suggest that central banks should follow a *flexible opportunistic* inflation targeting approach if LRMN does not hold and should not react to small inflationary shocks. Thus, they can avoid causing long-run damage to the real economy. Instead, they should wait for another exogenous shock to take inflation back to the vicinity of its target rate. Of course, a monetary restriction is unavoidable if the inflationary shock is large. However, they should react to deflationary shocks with monetary expansions, even if the shocks are small as they might lead to long-run real benefits. The results of this paper serve as arguments in favor of the policy of price-level targeting (Svensson, 1999; Gaspar et al., 2010) or its state-contingent variant (Evans, 2012; Bernanke, 2019). This policy requires the central bank to target the *average* rate of inflation instead of the actual one, thus compensating periods of below-average inflation with subsequent periods of above-average inflation. According to this paper's results, this policy of maintaining loose monetary conditions until the price level returns to its targeted path after a demand-side recession, such as the global financial crisis of 2008, may successfully restore the long-run damage caused by the demand shock in the real economy.

Recently, a few New Keynesian DSGE models have been developed to study the long-run real effects of monetary shocks generated by demand–supply interactions (Galí, 2020; Jorda et al., 2020; Garga and Singh, 2021). The usual policy implication of these models is that central banks should target additional real variables besides the usually targeted inflation rate and output gap to approximate the optimal monetary policy under LRMNN. Depending on the exact nature of demand–supply interactions that lead to the failure of LRMN, the employment or unemployment rate (Galí, 2020) or the cumulative deviation of the growth rate of total factor productivity (TFP) from its steady-state value (Garga and Singh, 2021) may serve as appropriate additional targets. Compared to these New Keynesian models, this paper comes up with four novel contributions as follows:

1. In the cited models, nominal rigidities are modeled according to the Calvo (1983) model of sticky price adjustment, which is well-known to be at odds with many empirical observations regarding micro-level price adjustment (Klenow and Kryvtsov, 2008; Nakamura and Steinsson, 2008). To the best of the author's knowledge, the model presented in this paper is the first among those developed for studying LRMNN, which is based on insights borrowed from the literature of menu cost models. The menu cost assumption makes it possible to model price adjustment based on more sophisticated microfoundations than the Calvo (1983) model. It allows the model to reproduce all important empirical observations regarding micro-level price adjustment, resulting in better-founded estimates for the real effects of monetary shocks.

2. The menu cost assumption makes it possible to model price adjustment's nonlinear and asymmetric nature (Karádi and Reiff, 2019), which is inherited by the long-run real effects of monetary shocks. Specifically, it allows the analysis of how the size and the sign of a monetary shock influence its long-run effectiveness.
3. It investigates the role of nonlinear price adjustment besides demand–supply interactions in determining the long-run real effects of monetary shocks.
4. The applied methodology of agent-based simulations and the agent-based features of the model can also be considered novelties. They contribute to the stronger microfoundations of the model and address some concerns raised by heterodox scholars of economics regarding DSGE models.

The rest of the paper is organized as follows. Section 2 summarizes related literature. Section 3 presents the dataset used to derive the empirical distributions related to micro-level price adjustment and the key properties of the distributions, which the model should reproduce. The hybrid menu cost model and its calibration are presented in Section 4. In Section 5, the model is used to estimate the long-run real effect of a standard monetary shock. The key mechanisms responsible for determining the long-run real effect are studied in Section 6. Section 7 analyzes how its size and its sign influence the long-run effectiveness of a monetary shock. Section 8 concludes the paper.

2. Related literature

The research is related to four different fields of the economic literature: post-Keynesian monetary macroeconomics, DSGE-type menu cost models, agent-based economic modeling, and New Keynesian models of long-run monetary non-neutrality.

2.1. Post-Keynesian monetary macroeconomics

To study the long-run real effects of monetary shocks, one must find economic mechanisms that can potentially explain them. Such mechanisms can most easily be found in the post-Keynesian literature, as post-Keynesians have never believed that money is neutral in the long run (Davidson, 1987, 1988; Cottrell, 1994). The literature mentions two economic mechanisms that may explain the violation of LRMN: nonlinear price adjustment and the presence of demand–supply interactions in the economy (Palacio-Vera, 2005; Fontana, 2007; Fontana and Palacio-Vera, 2007; Kriesler and Lavoie, 2007).

2.1.1. Nonlinear price adjustment

Within an intermediate range of the output gap, prices do not adjust to exogenous shocks; therefore, the short- and long-run Phillips curves are horizontal (Palacio-Vera, 2005; Kriesler and Lavoie, 2007). The following are the two most popular post-Keynesian explanations for this nonlinearity in price adjustment. First, in a fundamentally uncertain economic environment (Keynes, 1921; Knight, 1921), firms perceive a range of capacity utilization rates as normal, none of which induces any demand-led pressure to change prices. Second, decreasing returns do not prevail in the vicinity of potential output; hence, demand shocks lead to price adjustment only if they are large enough for decreasing returns to appear in production.

2.1.2. Demand–supply interactions

Potential real economic activity is path-dependent; fluctuations in the output gap (determined by aggregate demand) affect the potential output (aggregate supply)[3] (Palacio-Vera, 2005; Fontana, 2007; Fontana and Palacio-Vera, 2007; Kriesler and Lavoie, 2007). This positive feedback from actual toward potential real activity can manifest itself through three possible channels:[4]

1. *Labor force*: Large negative demand shocks may increase long-term unemployment. The loss of skills for the long-term unemployed reduces their employability, decreasing 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 reemployment (Blanchard and Summers, 1986, 1987; Galí, 2015, 2020).
2. *Capital stock*: If firms must face sunk adjustment costs related to market entry (Baldwin and Krugman, 1989; Dixit, 1989, 1992) or the initiation of their investment activities (Bassi and Lang, 2016), then as the demand shock dies away, the capital stock may not return to its initial value, leading to lower potential output. The interdependence between profits and investments may also lead to a permanently smaller capital stock when firms' profitability is low, such as during recessions (Arestis and Sawyer, 2009). This may also slow down technological progress as innovations are often manifested in the form of capital goods (Solow, 1960).
3. *Technological progress*: If technological progress is endogenous, it may also slow as a result of a positive feedback from short-run economic growth to the growth rate of productivity, known as the Kaldor-Verdoorn law (Verdoorn, 1949; Kaldor, 1957; Setterfield, 2002; Dutt, 2006; Storm and Naastepad, 2012). It captures the weakening of learning by doing and firms' reduced profit incentives to engage in research and development during recessions.

These effects work in the opposite direction for positive demand shocks.[5,6]

2.2. DSGE-type menu cost models

The first post-Keynesian explanation for the failure of LRMN, nonlinear price adjustment is present in numerous New Keynesian macro models as well but with a different interpretation according to which firms have to face fixed adjustment costs when they change their prices (Barro, 1972; Sheshinski and Weiss, 1977; Akerlof and Yellen, 1985; Blanchard and Kiyotaki, 1987). These fixed costs of price adjustment are usually labeled as *menu costs* (Mankiw, 1985). They lead to the appearance of an inaction band around the flexible-price level of output, within which firms will not adjust their prices in response to demand shocks, as the menu cost will probably not be compensated by the benefits of price adjustment. The rest of the paper will mostly refer to the menu cost interpretation of nonlinear price adjustment for two reasons. First, it has become more popular thanks to the success of menu cost models. Second, the model presented in Section 4 builds on many insights borrowed from the menu cost literature.

[3] This positive feedback is often labeled as *demand-led growth* or *hysteresis* in the post-Keynesian literature (Fontana, 2007; Fontana and Palacio-Vera, 2007; Kriesler and 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 have permanent effects on its steady state (Amable et al., 1993; Cross, 1993; Göcke, 2002). The possible mechanisms behind hysteresis include demand–supply interactions, but other mechanisms may also result in hysteretic macrodynamics (Setterfield, 2009).

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

[5] However, the empirical evidence for the effects of positive demand shocks on potential real economic activity is weaker than that for the effects of negative ones (Ball, 2009).

[6] There is little empirical evidence about the relative importance of the three mentioned channels in generating LRMNN, but the estimates of Jorda et al. (2020) suggest that demand–supply interactions through capital accumulation may be the most important one. According to their estimates, it is followed by the TFP channel, while the labor force channel plays practically no role in generating LRMNN.

The existence of menu costs is not the only New Keynesian explanation for the rigidity of prices. Other explanations include predetermined prices (Phelps and Taylor, 1977) or wages (Fischer, 1977; Taylor, 1979), information frictions (Mankiw and Reis, 2002), frictions of consumer search (Cabral and Fishman, 2012), and the fairness considerations of consumers (Rotemberg, 2005). All of these have proven useful in explaining some empirical features of micro- or macro-level price adjustment. However, Klenow and Kryvtsov (2008) argued that state-dependent menu cost models can be more successful in reproducing the most important empirical regularities of micro-level price adjustment than time-dependent models, in which the occurrence of a price change depends only on the time spent since the last price change and not on the states of individual firms. Levy et al. (1997) and Dutta et al. (1999) measured the magnitude of menu costs in large U.S. retail chains directly and found that although the costs of printing price tags are small, there are substantial labor costs related to price adjustment. In the case of a large industrial firm, Zbaracki et al. (2004) measured the managerial costs of making pricing decisions, the costs of informing customers, and negotiating new prices and found them to be even larger than the physical costs of price adjustment. These types of costs can be expected to remain important even in the era of digitalization, when the physical costs of price adjustment will probably decrease. Slade (1998), Aguirregabiria (1999), and Stella (2014) inferred the magnitude of menu costs from the price observations of goods sold in grocery stores using structural econometric estimations and found it to be non-negligible. Akerlof and Yellen (1985), Mankiw (1985), and Dixit (1991) argued that even small menu costs can result in large business cycles. Considering their results, the practical relevance of the menu cost assumption seems to be well-grounded, even if it is compared to alternative explanations of imperfect price adjustment.

Nowadays, the menu cost assumption usually appears in DSGE models, and DSGE-type menu cost models have become the standard tools for analyzing the *short-run* real effects of monetary shocks (Golosov and Lucas, 2007; Gertler and Leahy, 2008; Nakamura and Steinsson, 2010; Midrigan, 2011; Alvarez et al., 2016; Karádi and Reiff, 2019). However, within their framework, money is neutral in the long run despite the nonlinearity of price adjustment caused by the assumption of menu costs. This contradicts the views of some post-Keynesian macroeconomists (Palacio-Vera, 2005; Kriesler and Lavoie, 2007).

All of the cited DSGE-type menu cost models are heterogeneous-agent DSGE models with similar structures. The demand side of these models comprises an optimizing representative household, whose nominal income is assumed to be proportional to the nominal money supply; the central bank exogenously determines the latter. The supply side of the models consists of a continuum of ex-ante homogenous but ex-post heterogeneous firms. This means that firms follow the same dynamically optimal pricing decision rule. However, they still make different individual decisions because they are hit by idiosyncratic productivity shocks, the realizations of which differ ex-post. The assumed shape of the idiosyncratic shock distribution as well as the assumption of multi-product firms are crucial for reproducing the shape of the empirical distribution of nonzero price changes, which, in turn, substantially influences the real effects of monetary shocks in menu cost models (Midrigan, 2011; Alvarez et al., 2016).

Agent-based economic modeling

Agent-based models are becoming increasingly popular tools in macroeconomic research[7] (Leijonhufvud, 2006; Fagiolo and Roventini, 2017; Dawid and Delli Gatti, 2018; Dosi and Roventini, 2019; Haldane and Turrell, 2019), and specifically in monetary macroeconomics (Delli Gatti et al., 2005; Salle et al., 2013; Dosi et al., 2015; Salle, 2015). An agent-based model is "*a model, in which a multitude of (heterogeneous) elements interact with each other and the environment*" (Dawid and Delli Gatti, 2018, p. 67). Agent-based computational economics (ACE) is the application of agent-based modeling to economics or "*the computational study of economic processes modeled as dynamic systems of interacting agents*" (Tesfatsion, 2006, p. 835). Standard assumptions of an ACE macro model include a large number of boundedly rational, heterogeneous agents instead of a perfectly rational, representative one and a disequilibrium market mechanism with direct local interactions of agents (Dosi, 2012; Fagiolo and Roventini, 2017). Setterfield and Gouri Suresh (2016) argued that agent-based models are especially useful for studying path-dependent macrodynamics generated for instance by demand–supply interactions as many path-dependent phenomena are *emergent*. They cannot be observed at the micro-level of the economy, but they "emerge" at the macro level as the result of interactions between heterogeneous microeconomic agents. Agent-based models have been developed for the analysis of such emergent phenomena (Tesfatsion, 2006).[8]

Few agent-based models try to assess the differences between DSGE and ACE models by building on insights from both modeling traditions (Salle et al., 2013; Salle, 2015; Dilaver et al., 2018; Guerini et al., 2018; Gobbi and Grazzini, 2019). The model presented in this paper is related to these, but it cannot purely be labeled as an agent-based model because of its hybrid nature. From a methodological perspective, the model developed in this paper most closely relates to the one presented by Babutsidze (2012), which is an otherwise standard menu cost model also studied via agent-based simulations. Delli Gatti et al. (2005) presented an example of an agent-based macro model in which LRMN fails because the central bank is assumed to influence the economy through its *supply* side by determining the credit costs of financing production.

New Keynesian models of long-run monetary non-neutrality

New Keynesian models of long-run monetary non-neutrality: In New Keynesian models of LRMNN, the long-run real effects of monetary shocks are the results of one of the following two types of demand–supply interactions: an insider-outsider mechanism of wage bargaining (Galí, 2020) or endogenous technological progress (Jorda et al., 2020; Garga and Singh, 2021). Their magnitude turns out to be economically significant under realistic calibrations.

3. The empirical data

Before presenting the hybrid menu cost model, it is important to summarize the empirical observations that the model is required to reproduce. Its empirical performance will be assessed by analyzing how well it fits key moments of two empirical distributions related to product-level price adjustment: the distribution of nonzero price changes and the frequency distribution of price changes.

These two empirical distributions are derived from a micro-level dataset often applied for calibrating menu cost models, the Dominick's dataset (Midrigan, 2011; Alvarez et al., 2016). It consists 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 nine

[7] The most popular medium-scale agent-based macroeconomic models include the Complex Adaptive Trivial Systems (CATS) model (Delli Gatti et al., 2011; Assenza et al., 2015), the EURACE model (Deissenberg et al., 2008; Dawid et al., 2019), the Keynes + Schumpeter (K + S) model (Dosi et al., 2010, 2017), and the Java Agent-Based MacroEconomic Laboratory (JAMEL) (Seppecher, 2012; Seppecher and Salle, 2015). Some important small-scale agent-based macro models can be found, for instance, in Lengnick (2013), Gaffeo et al. (2015), and Guerini et al. (2018).

[8] Examples of agent-based models developed for studying a specific form of path-dependency, hysteresis are presented by Bassi and Lang (2016) and Dosi et al. (2018).

years (1989–1997) of weekly store-level data regarding the prices of 9450 products collected in 86 Dominick's Finer Foods retail chain stores in the Chicago area. As prices are highly correlated across stores, Midrigan (2011) decided to work with prices from one store with the largest number of observations. He has made the resulting dataset available in the supplemental material to his paper, which is the dataset used in this paper. The data were collected during a period of no substantial economic turmoil in the U.S. Thus, the calibrated model will estimate the long-run real effects of monetary shocks during normal times.

The model presented in Section 4 does not contain any incentives for firms to engage in temporary sales; therefore, the data are sales-filtered using the algorithm developed by Kehoe and Midrigan (2008) to obtain time series about regular prices.[9] The resulting weekly time series of regular prices is time-aggregated to monthly frequency by only keeping every fourth observation. The monthly frequency of the resulting sample is closer to the quarterly frequency of GDP data that will be used to estimate some model parameters. This leaves a sample of 100 months of regular prices for 9450 different products. As per Midrigan (2011), only price observations for which the calculated regular price equals the observed price are kept. Finally, all regular price changes are computed as the log difference of subsequent monthly prices. Following Midrigan (2011), all regular price changes with a size greater than the 99th percentile of their size distribution are dropped to eliminate outliers. The final sample consists of 22,630 observations of nonzero monthly regular price changes.

The first step to derive the frequency distribution of empirical price changes is to calculate the frequency of monthly regular price changes for each of the 9450 products. This is achieved by dividing the number of months in which the product's price has changed by the number of months for which the price observation and the previous month's observation are not missing. Then, all products with a calculated frequency of 0 are dropped, as it seems unlikely that the price of a product does not change for nine years. Missing values are the most probable reason for not registering any price changes for these products. Finally, all products with a frequency of price changes greater than the 99th percentile of the frequency distribution are dropped to eliminate outliers.[10] The final sample consists of the frequencies of regular price changes for 7765 products.

Fig. 1 presents the two empirical distributions. The probability density functions of the normal distribution with equal means and variances are superimposed; they serve as benchmarks that help make the empirical distributions' properties visible. Graphical inspection of Fig. 1, supplemented with calculating key moments of the two distributions, reveals some important empirical features of micro-level price adjustment that the model should reproduce. While calculating the moments, all price changes and all frequencies of price changes related to a certain product are weighted with the share of that product in the basket of the average Dominick's customer.[11]

The empirical observations (EO) that the model will be required to reproduce are listed below,[12] reported together with the values of the moments related to the observations. All of these moments will be targeted during the calibration of the hybrid menu cost model.

- **EO1**: *The mean size of price changes is large* (9.7%). The model needs to reproduce this observation for the strength of price adjustment to be realistic within its framework.
- **EO2**: Still, *many price changes are small.* Specifically, 28.9% of all price changes are smaller than half of the mean size of price changes. This moment will be useful in fine-tuning the correlation between productivity shocks hitting different goods supplied by the same firm in the model.
- **EO3**: 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) proved that it is crucial for all menu cost models to reproduce the empirical kurtosis of nonzero price changes as it sufficiently summarizes information about the strength of the so-called *selection effect*, that is, 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 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 short-run real effects of monetary shocks in menu cost models (Caplin and Spulber, 1987; Golosov and Lucas, 2007; Midrigan, 2011). It seems reasonable to suspect that it also strongly influences the long-run real effects once they are brought to life by an appropriate mechanism.
- **EO4**: *The standard deviation of price changes is large* (12.5%). This moment will be used to pin down the standard deviation of idiosyncratic productivity shocks in the model.
- **EO5**: *The mean nonzero price change is* 1.9%. This moment will be useful for generating a realistic rate of trend inflation in the model.
- **EO6**: *Price increases are more frequent than price decreases.* Specifically, 66.0% of all price changes are price increases.
- **EO7**: *The mean size of price decreases* (11.0%) *is larger than that of price increases* (9.0%); the latter is 81.8% of the former. EO6 and EO7 are important to reproduce if the asymmetry between the real effects of positive and negative monetary shocks is to be analyzed.
- **EO8**: *Price changes are rare* for the average product. The mean monthly frequency of price changes is 11.6%. This moment is important to be reproduced by the model to generate a realistic degree of price stickiness. According to Alvarez et al. (2016), it is the other key moment, along with the kurtosis of the distribution of nonzero price changes that determines the 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.
- **EO9**: *The frequency distribution of price changes is skewed to the right.* The prices of most products change in around 5%–15% of the months, but some products have price change frequencies above 30%. The skewness of the distribution is equal to 0.62. This information will help the model generate a realistic degree of heterogeneity in the frequencies of price changes.

4. The hybrid menu cost model

This section presents the hybrid menu cost model and its calibration.

4.1. General properties of the model

Before going into the details of the model, it is worth summarizing the key properties that make it a hybrid post-Keynesian-DSGE-agent-based menu cost model. Its general structure mimics that of DSGE-type menu cost models, which can answer how large short-run real effects emerge at the macro level of the economy because of heterogeneous micro-level price adjustment to monetary shocks. Hence, after some appropriate

[9] The Matlab codes for the sales-filtering algorithm and 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.

[10] As the number of observations available to calculate the frequencies of price changes is different for each product, all frequencies of price changes are weighted with the number of observations available to calculate them while computing the percentiles of the frequency distribution.

[11] The frequencies of price changes are also weighted with the number of observations available to calculate them, as it is different for each product because of the missing values present in the dataset.

[12] These empirical observations can be considered as standard: they have all been reported before in the empirical literature of sticky price adjustment (Bils and Klenow, 2004; Klenow and Kryvtsov, 2008; Nakamura and Steinsson, 2008). Müller and Ray (2007) and Chen et al. (2008) present detailed empirical evidence for the two observations concerning asymmetric price adjustment (EO6 and EO7) using the Dominick's dataset.

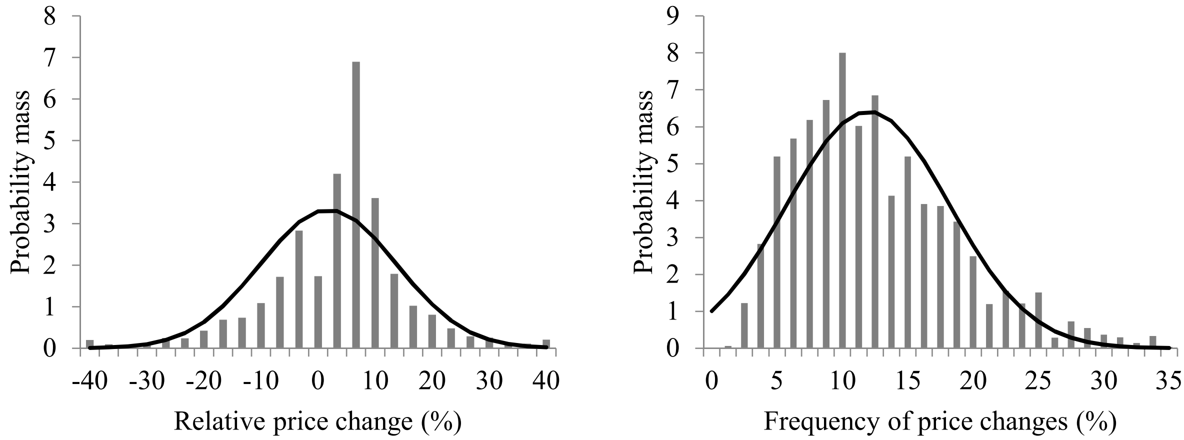

Fig. 1. The empirical distributions of nonzero price changes (left panel) and of the monthly frequencies of price changes (right panel).
Note: Both histograms are based on the data available in the supplemental material to Midrigan (2011), which have been sales-filtered, time-aggregated to monthly frequency, and cleared of outliers. Superimposed are the probability density functions of the normal distribution with equal means and variances.

amendments, their structure seems to be a natural starting point for studying the connections between heterogeneous micro-level price dynamics and the long-run real effects of monetary shocks.

An economy's goods market is modeled, the demand side of which comprises a perfectly rational representative household.[13] The supply side consists of N heterogeneous, monopolistically competitive firms, each selling G different types of goods. All product varieties sold in the market are differentiated from each other. The model exhibits all the important characteristics of DSGE-type menu cost models summarized in Section 2.2, except the ex-ante homogeneity and the perfect rationality of firms.[14] It contains both economic mechanisms that may lead to the failure of LRMN according to post-Keynesian monetary macroeconomics: nonlinear price adjustment and demand–supply interactions. To the best of the author's knowledge, these post-Keynesian features make this the first menu cost model suitable for studying the long-run real effects of monetary shocks besides their short-run ones.

The model's behavior is studied via agent-based simulations. Still, it cannot purely be labeled as an agent-based model because it lacks one of the core ingredients of ACE models: the direct local interactions between agents. Firms interact *globally* in the model by affecting the dynamics of market aggregates, which feed back into micro-level pricing decisions.[15] This simplification serves comparability with DSGE-type models and can be relaxed in future research steps.

Still, the model shares several common features with agent-based economic models. The most important is that it contains a multitude of heterogeneous, boundedly rational firms, the interactions of which are analyzed via agent-based simulations. Each firm's pricing decision is explicitly simulated, and they are aggregated numerically to assess how large long-run real effect unfolds after a monetary shock as a macro-level emergent phenomenon resulting from the global interactions between these heterogeneous micro-level pricing decisions.

The assumption of bounded rationality is in line with the views of Simon (1955, 1956), with the perspective of post-Keynesian economics (Lavoie, 2014) and with the spirit of ACE (Tesfatsion, 2006; Dosi, 2012; Fagiolo and Roventini, 2017). Firms are assumed to not have perfect knowledge about their market environment because of their decision makers' cognitive limitations. Additionally, the complexity of the environment makes it impossible to gather all the relevant information necessary for making optimal choices. This paper regards boundedly rational decision-making the same way as Simon (1955, 1956). Because of the firms' inability to make optimal decisions, they use *heuristics*, that is, simple *rules of thumb,* for making decisions. Heuristics allow firms to easily arrive at decisions being in line with their profit-maximizing motivations by simplifying the decision problem (Gigerenzer, 2008; Hommes, 2013). In this sense, the choices made are satisfying but not optimal.[16][17]

There are two motivations behind the assumption of bounded rationality in the model. First, according to the experimental evidence of behavioral economics (Tversky and Kahneman, 1974; Camerer et al., 2004), it describes how economic decisions are made in reality better than the perfectly rational pricing behavior assumed in DSGE-type menu cost models. Second, it substantially reduces the mathematical and computational burden of analyzing the model by eliminating the need to numerically solve complicated dynamic optimization problems in a heterogeneous-agent DSGE framework. Despite the simpler mathematical structure of the model, its empirical performance will be shown to be just as good as that of DSGE-type menu cost models in Subsection 4.6.[18]

The reduced computational burden opens the way for another ACE feature to be included in the hybrid menu cost model, making it possible to assume that firms are ex-ante heterogeneous, not just ex-post, as in most DSGE-type menu cost models. Firms are assumed to be permanently different concerning their price adjustment thresholds. This allows the model to reproduce the shape of the frequency distribution of price

[13] Assuming the existence of a perfectly rational representative household is rather unusual in an economic model with agent-based features, but it facilitates the comparability of the model structure to that of 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.

[14] However, a variant of the model with dynamically optimizing firms is presented in Subsection 6.1 to show that the key qualitative findings hold under the assumption of perfectly rational firms as well.

[15] See Brock and Durlauf (2001) for a distinction between local and global interactions.

[16] In a post-Keynesian approach, bounded rationality can be grounded with the assumption that firms face fundamental uncertainty (Keynes, 1921; Knight, 1921) because of the limited human abilities/characteristics (O'Donnell, 2013) of their decision makers.

[17] I do not want to suggest that firms are less rational in reality than households. The assumption of perfect rationality in the case of the representative household serves convenience only. It does not play a key role in determining the model's conclusions, while facilitating comparison with DSGE-type menu cost models.

[18] In addition, the model will be able to reproduce the shape of the frequency distribution of empirical price changes. This is not the case with most DSGE-type menu cost models.

changes. DSGE-type menu cost models usually match only the mean.[19] The modeled goods market carries some sort of disequilibrium characteristics, which also exhibit similarities with ACE models. Firms cannot perfectly coordinate demand with the supply of their products because of their bounded rationality; hence, the submarkets of individual product varieties will always be in short-run disequilibrium even in the absence of price rigidity, inducing further price adjustments in the future.

4.2. The demand side of the market

The demand side of the market is assumed to consist of a perfectly rational representative household that behaves according to the Dixit-Stiglitz model of monopolistic competition (Dixit and Stiglitz, 1977). The household decides the demanded quantities of different product varieties in a way that maximizes its utility, subject to its budget constraint:

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

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

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

where c stands for the consumed quantities, and p represents 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 household's utility, 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.[20] The budget constraint expresses that total spending on different product varieties has to be equal to the household's nominal income.

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

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

where the price level in period t is given by the CES price index $P_t = (\sum_{i=1}^{N} p_{i,t}^{1-\varepsilon})^{\frac{1}{1-\varepsilon}}$, and the firm-level price index is $p_{i,t} = (\sum_{g=1}^{G} p_{i,g,t}^{1-\gamma})^{\frac{1}{1-\gamma}}$. These definitions of the price indices imply that nominal aggregate expenditure will be equal to P_tC_t. The demanded quantity of a product variety decreases ceteris paribus if it becomes more expensive than other varieties supplied by the same firm, and the household wants to buy less from a particular firm if its price index increases relative to the market price level.[21] Finally, a rise in the household's real income increases the demanded quantities of all product varieties, assuming that their relative prices remain unchanged.

The household's nominal income is determined by monetary policy: the central bank is assumed to control nominal aggregate demand according to an exogenous stochastic process.[22][23] Let g_t^Y denote the gross growth rate of nominal aggregate demand in period t, that is, $g_t^Y = Y_t/Y_{t-1}$. The growth rate of nominal aggregate demand is assumed to follow a first-order autoregressive (AR(1)) process:[24]

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

where $\overline{g}^Y$ 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 monetary shock in period t.

4.3. The supply side of the market

The paper now departs from the assumptions of the Dixit-Stiglitz model and begins implementing the model's post-Keynesian and agent-based features. The supply side of the market is populated by N heterogeneous, monopolistically competitive firms, which are the agents in the model.

Each firm is assumed to have a *supply potential* $\overline{q}_{i,g,t}$ for all supplied product varieties, which are allowed to change over time. The supply potential of a product is the amount of its output that its producer strives to sell. Boundedly rational firms are assumed *not* to know demand functions (1) and AR(1) process (2) of nominal demand growth, but they are assumed to know their own cost structures. In such a situation of imperfect information, the supply potential of a product variety cannot be anything else but the amount of output, at which it is the most cost-efficient to be produced. In a post-Keynesian perspective, the supply potential can also be interpreted as the output corresponding to the normal capacity utilization rate. In the model, macro-level potential output is the aggregate of micro-level supply potentials.[25]

[19] An exception is the multisector DSGE-type menu cost model of Nakamura and Steinsson (2010), in which different sectors of the economy are ex-ante heterogeneous as they face different amounts of menu costs. However, the number of sectors is limited to 14 as the computational burden of solving 14 dynamic profit-maximization problems simultaneously in a heterogeneous-agent DSGE framework is already heavy. There are no such limitations in an agent-based framework as the bounded rationality of the decision rules makes the computational burden of having a large number of ex-ante heterogeneous agents tolerable.

[20] Y_t could also be labeled as the nominal money supply if the income velocity of money was assumed to be equal to 1. Considering that a period in the model corresponds to a month, such an assumption would not be unrealistic at all. Following Nakamura and Steinsson (2010), the term *nominal aggregate demand* is used for Y_t.

[21] This results in global interactions (Brock and Durlauf, 2001) between firms' price-setting behavior similar to those present in the coordination failure model described by Cooper and John (1988). If demand depends on the price level, then the pricing decisions of individual firms will indirectly influence each other. In the spirit of ACE, the macro price level as an emergent phenomenon will feed back into micro-level pricing decisions (Tesfatsion, 2006).

[22] The exact channels of monetary transmission are not crucial to be modeled for the purpose of the research. It is of secondary importance if the central bank controls the interest rate or the money supply; the only important assumption is that the central bank is able to induce changes in nominal aggregate demand. The focus will be on the real effects of these changes.

[23] This assumption is a shortcut for the usual practice followed in DSGE-type menu cost models, according to which the form of the utility function is chosen in a way that assures nominal income will be proportional to nominal money supply in the case of optimal behavior. See Golosov and Lucas (2007) for the necessary restrictions on the utility function.

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

[25] The term *supply potential* is borrowed from Arestis and Sawyer (2009).

Firms decide their prices simultaneously using a heuristic rule.[26] The rule follows their motivation to produce close to the supply potentials of their products as it helps coordinate demand with them. The presence of menu costs implies that it is not worth changing the prices if demanded quantities are anticipated to be close to the supply potentials, as the loss implied by the menu cost would probably offset the potential gains of price adjustment. In line with DSGE-type menu cost models with multi-product firms, firms are assumed to enjoy economies of scope in price adjustment; if they pay the menu cost, they can reprice all their products, even those that are only slightly mispriced.[27] This assumption helps generate a realistic amount of small price changes in the model (Midrigan, 2011; Alvarez et al., 2016; Karádi and Reiff, 2019).

In line with DSGE-type menu cost models, production is assumed to be demand-determined; thus, produced quantities $q_{i,g,t}$ are equal to demanded quantities: $q_{i,g,t} = c_{i,g,t}$ for $\forall i, g, t$.[28] This implies that there are no inventories or shortages of any product variety, which can be interpreted as assuming that the goods supplied in the market are perishable.[29]

Before making pricing decisions, firms create expectations about excess demand $\widehat{q}_{i,g,t}$ for each of their supplied products. This is achieved by computing the relative deviation of its anticipated demand-determined output from its supply potential:

$$\widehat{q}^{e}_{i,g,t} = \frac{q^{e}_{i,g,t} - \overline{q}_{i,g,t}}{\overline{q}_{i,g,t}},$$

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

Pricing decisions are governed by the anticipated value of an index that measures the average extent of disequilibrium in the submarkets of the product varieties supplied by firm i. The anticipated value of the *disequilibrium index* of firm i in period t is denoted by $\widehat{q}^{e}_{i,t}$ and is calculated as

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

where $\theta \in [0,\ 1]$ measures the asymmetry of price adjustment, and $I()$ is the indicator function that returns 1 if anticipated excess demand for good g is negative and returns 0 otherwise. It is assumed that $\theta > 0$; thus, when firms create expectations about the value of the firm-level disequilibrium index, they assign lower weights to products for which they expect excess supply. The reason for this is that although firms do not know the specific form of AR(1) process (2) governing nominal aggregate demand, they are assumed to be able to observe the inflation rate; hence, they are aware that there is trend inflation in the economy ($\overline{g}^{Y} > 1$). In the presence of trend inflation, the relative price of a product falls, even if its nominal price is unchanged. Under such circumstances, the anticipated excess supply required by a firm to decrease the price of a product is larger than the anticipated excess demand required to increase it. This way, the firm can save on the menu cost by letting trend inflation move the relative prices of its products with anticipated excess supply in the desired direction.[30]

The presence of menu costs leads to the appearance 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, that is, the anticipated value of the disequilibrium index, above which the firm changes the prices of its products. This threshold value is assumed to be ex-ante heterogeneous across firms. A possible explanation is that firms differ in the amounts of menu costs they face. The value of z_i is not determined by menu costs alone; it may also depend on the time preferences of the firm's decision makers or their perceptions about the uncertainty of the market environment. Nevertheless, it is reasonable to assume that the threshold depends positively on the amount to be paid for menu costs.

The heuristic pricing decision rule can be written as

$$p_{i,g,t} = \begin{cases} p_{i,g,t-1}\left(\dfrac{q^{e}_{i,g,t}}{\overline{q}_{i,g,t}}\right)^{\alpha^U}, & \text{if } \widehat{q}^{e}_{i,t} > z_i \text{ and } \widehat{q}^{e}_{i,g,t} > 0 \\ p_{i,g,t-1}\left(\dfrac{q^{e}_{i,g,t}}{\overline{q}_{i,g,t}}\right)^{\alpha^D}, & \text{if } \widehat{q}^{e}_{i,t} > z_i \text{ and } \widehat{q}^{e}_{i,g,t} < 0 \\ p_{i,g,t-1}, & \text{if } \widehat{q}^{e}_{i,t} \leq z_i \end{cases} \tag{3}$$

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 pricing decision rule (3), firm i keeps its prices unchanged if the anticipated value of its disequilibrium index does not exceed its price adjustment threshold. Otherwise, it will adjust its prices based on anticipated excess demand. If firm i expects demand for its good g to be greater than its supply potential, it will raise its price to decrease demanded quantity. In the opposite case, the firm will lower the price to increase the demanded quantity. The sizes of price changes are regulated by parameters α^U and α^D.[31] As price decreases are larger than price increases empirically, according to EO7 reported in Section 3, it is expected that the value of α^U will turn out to be smaller than α^D during the calibration. 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 steal consumers from competitors. Finally, note that pricing decision rule (3) is general enough to be consistent with the New Keynesian interpretation of nonlinear price adjustment (menu costs) and also with its post-Keynesian interpretations mentioned in Section 2.1.1, that is, fundamental uncertainty and the lack of decreasing returns near

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

[27] Lach and Tsiddon (2007), Midrigan (2011), and Stella (2014) present empirical evidence for economies of scope in price setting. The latter two studies are based on the Dominick's dataset.

[28] This assumption, together with assuming the existence of a representative household, allows one to set aside the explicit modeling of direct local interactions between firms and households, thereby facilitating comparison with DSGE-type menu cost models.

[29] Allowing for the presence of inventories would be an interesting way of extending the model. It would potentially make the real effects of monetary shocks dependent on the existing stock of inventories. For example, a large stock of inventories would probably make the increase in production necessary to fulfill the additional demand generated by a positive monetary shock weaker than the increase necessary when inventories are low.

[30] Assuming a perfectly rational single-product firm, Ball and Mankiw (1994) showed that the gap required between the actual and the desired price to induce price adjustment is larger in cases of price decreases than increases, if there is an inflation trend in the economy. Their idea is generalized to a multiproduct setting. The other important difference is that this paper does not assume that the asymmetry of price adjustment measured by θ is optimally chosen. Its value will be calibrated to match the empirical fraction of price increases among all nonzero price changes.

[31] The assumed pricing decision rule conditional on adjustment is inspired by Kornai and Martos (1973), who assume that firms decide about production based on excess demand, which is proxied by the difference between the actual and the desired amount of their inventories. Duménil and Lévy (1991) assume the same decision rule for prices. In post-Keynesian and agent-based models, it is also standard to assume that prices or markups react to excess demand either directly (Solow and Stiglitz, 1968; Leijonhufvud, 2006; Guerini et al., 2018; Nishi and Stockhammer, 2020) or indirectly through the deviation of the actual amount of inventories from the desired one (Lengnick, 2013; Gaffeo et al., 2015).

the supply potential.

The individual price adjustment thresholds are drawn from a lognormal distribution. It is an asymmetric probability distribution; hence, it allows the model to reproduce EO9, according to which, the frequency distribution of price changes is skewed to the right. Specifically, it is assumed that

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

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

Firms are assumed to use a very simple adaptive rule to form their expectations about demand. They expect that demanded quantities in the current period will be equal to the quantities demanded in the previous period, as follows:[32]

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

Two stochastic processes determine the evolution of supply potentials. It is assumed that the supply potential of good g produced by firm i in period t can be decomposed into two components as

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

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 goods-specific component of the supply potential, independent across firms but correlated across goods produced by the same firm and in time.

Let $g^\mu_t = \mu_t/\mu_{t-1}$ denote the gross growth rate of the aggregate component. Its evolution is assumed to be determined by the following equation:

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

where $\overline{g}^\mu > 0$ is the gross potential growth rate of the economy in a steady state, $Q_t = \left(\sum_{i=1}^{N} q_{i,t}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}$ is real aggregate output computed as the CES aggregate of the amounts of firm-level aggregate output, and $\overline{Q}_t = \left(\sum_{i=1}^{N} \overline{q}_{i,t}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}$ is macro-level potential output calculated as the CES aggregate of the amounts of firm-level potential output. 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 product varieties supplied by the firm, and firm-level potential output $\overline{q}_{i,t} = \left(\sum_{g=1}^{G} \overline{q}_{i,g,t}^{\frac{\gamma-1}{\gamma}}\right)^{\frac{\gamma}{\gamma-1}}$ is the CES aggregate of the supply potentials of 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 an aggregate productivity shock does not hit it, then the aggregate component of supply potentials grows at the rate of $\overline{g}^\mu - 1$. If the output gap is positive ($Q_t > \overline{Q}_t$), the potential growth rate rises above its steady-state value. If the output gap is negative ($Q_t < \overline{Q}_t$), the potential growth rate falls below its steady-state value. The strength of this interaction between demand-determined actual output and potential output (aggregate supply) is regulated by parameter η. The possible economic mechanisms behind demand–supply interactions are detailed in Section 2.1.2. Of course, the arrival of an aggregate productivity shock may overwrite the effects of the first two terms of Equation (4) on potential growth.

Demand–supply interactions are modeled with a macro-level equation that lacks explicit microeconomic foundations. Although this is a considerable simplification, it seems to be acceptable for two reasons. On the one hand, it seems reasonable to assume that a recessionary (booming) macroeconomic environment worsens (improves) the growth prospects of *all* firms, not just of those forced to produce below (above) the supply potentials of their products. As mentioned in Section 2.1.2, long-term unemployment increases (decreases) during recessions (booms), the quality and quantity of the active labor force deteriorate (develop), which is an aggregate effect, reducing (improving) the opportunities of all firms to hire workers with sufficiently strong skills. Aggregate productivity growth slows (accelerates) during recessions (booms), making it more difficult (easier) for all firms to benefit from knowledge spillovers, etc.[33] On the other hand, the post-Keynesian literature provides many examples for this method of modeling demand–supply interactions (Lavoie, 2006; Fontana and Palacio-Vera, 2007; Kriesler and Lavoie, 2007; Setterfield, 2009; Nishi and Stockhammer, 2020). DeLong and Summers (2012) also use an equation similar to Equation (4), while Jorda et al. (2020) model endogenous TFP growth similarly in a DSGE framework.

This modeling practice has advantages and disadvantages. One advantage is that it allows the researcher to draw more general conclusions. If one focuses on a specific microfounded mechanism that results in demand–supply interactions, one cannot determine whether the model outcomes hold for other mechanisms. This is a problem because it is still rather unexplored, which of the theoretically possible channels of demand–supply interactions are the most important in reality. Equation (4) is general enough to make it possible to clarify whether any microeconomic mechanism that results in significant demand–supply interactions leads to the failure of LRMN or not. Another advantage is that it allows one to develop a simple estimate for the strength of demand–supply interactions using macroeconomic data instead of micro-level observations. The disadvantage is that it does not allow to explain what determines the strength of demand–supply interactions; hence, the possible long-run real effects of monetary shocks that may unfold as their consequences. In this way, the model has limited ability to develop policy advice about influencing the long-run effectiveness of monetary policy. Therefore, an important direction of future research might be to develop detailed microfoundations for demand–supply interactions.[34] However, this paper will first examine if they matter at all.

The evolution of the goods-specific component of the supply potential is determined by the following AR(1) process:

[32] Gigerenzer and Brighton (2009) argued that the simplest heuristics are more successful in fundamentally uncertain environments than more sophisticated ones. Dosi et al. (2020) examined this idea within an agent-based macroeconomic model and found that the simple adaptive rule that this paper assumes for forming demand expectations beats the forecasting performance of more sophisticated rules, such as least-squares learning.

[33] Equation (4) represents another manifestation of global interactions (Brock and Durlauf, 2001) between firms, which take the form of positive spillover effects similar to those described in the literature of coordination failures (Cooper and John, 1988): if the majority of firms produce below their supply potentials, it will affect the supply potentials of *all* firms negatively. In the spirit of ACE (Tesfatsion, 2006), macro-level potential output as an emergent phenomenon will feed back into micro-level pricing decisions.

[34] Dosi et al. (2010, 2018) came up with boundedly rational, disequilibrium microfoundations for demand–supply interactions in an agent-based macro model, while Anzoategui et al. (2019) and Garga and Singh (2021) developed perfectly rational, equilibrium microfoundations within DSGE frameworks.

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

where $\zeta_{i,g,t}$ is a random variable representing an idiosyncratic productivity shock hitting 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, crucially influencing the real effects of monetary shocks. Following Gertler and Leahy (2008) and Midrigan (2011), this paper assumes that the distribution of idiosyncratic productivity shocks is leptokurtic. This way, the model will reproduce the substantial excess kurtosis of the empirical distribution of nonzero price changes. Specifically, idiosyncratic productivity shocks are assumed to arrive infrequently, according to a Poisson process:

$$\tilde{\zeta}_{i,g,t} = \begin{cases} 0 & \text{with probability } 1-\lambda \\ N\left(0,\ \dfrac{\sigma_\zeta^2}{\left[1+\dfrac{\chi(2+\chi)}{G}\right]\lambda}\right) & \text{with probability } \lambda \end{cases},$$

where $\lambda \in [0,\ 1]$ is the probability that a nonzero shock arrives,[35] and $\chi > 0$ is a parameter to be introduced, 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 $\sigma_\zeta^2 / \{[1 + \chi(2 + \chi)/G]\lambda\}$.[36] It is proven, in Online 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.

Goods-specific productivity shocks are assumed to be uncorrelated across firms, but they are correlated across goods produced by the same firm. Within-firm correlation between goods-specific productivity shocks is modeled following Midrigan (2011). The actual realizations of goods-specific productivity shocks are determined as

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

In Online Appendix B, it is proven that to set the within-firm correlation of goods-specific productivity shocks to $\rho_\zeta \in [-1,\ 1)$, χ[37] must be determined as

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

In 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). A smaller correlation between goods-specific productivity shocks increases the fraction of small price changes in the model as the probability of large shocks hitting some goods, accompanied by small shocks hitting other goods, is higher. Under such realizations of goods-specific productivity shocks, price adjustment is induced by the large shocks, and small price changes are carried out for the goods hit by small shocks that have only been slightly mispriced.

4.4. Simulations

The model's nonlinearities and the different forms of heterogeneity do not allow for an analytical solution; hence, its behavior is studied via agent-based simulations. Simulations begin from situations where aggregate or idiosyncratic shocks do not hit the market, the actual quantities produced are equal to the supply potentials, and all variables are constant in time. The initial values of supply potentials are set 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 will be equal to 1, and prices also initially need to equal to 1.

The timeline of events within each period is as follows:

1. Nominal aggregate demand is determined after the central bank comes up with a realization for the monetary shock.
2. Firms discover the supply potentials of their products following the realizations of aggregate and idiosyncratic productivity shocks.
3. Firms decide about prices simultaneously.
4. The price level is calculated.
5. The household decides about demanded quantities. Production is demand-determined; the demand decision also determines the output of each product.
6. Aggregate statistics are computed. The most important statistics calculated at the end of each period are the 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.

The simulation is run for 1000 periods, sufficient for a steady-state joint distribution of relative prices and growth rates of supply potentials to emerge.[38] Then, the simulation is run for another T periods, and the first 1000 periods are discarded. This assures that the statistics from the simulated time series will not be biased by the initial adjustment toward a steady state.

In the case of simulating impulse response functions to monetary shocks, a similar procedure is followed. First, a $1000 + T$ period long baseline path is simulated for the variables without monetary shocks, but with aggregate and idiosyncratic productivity shocks present. Then, another path is simulated using the same random numbers but with a monetary shock of a given size arriving in period 1002. The percentage deviations are calculated between the two simulated paths of the variables, the first 1000 periods are discarded, and period 1001 is treated as period 0. This exercise is repeated 10,000 times, and the 10,000 time series for each variable is averaged out. The resulting time series approximate the conditional expectations for the deviations between the values of the variables on the baseline paths and on the paths hit by a monetary shock, where there are two conditions:

1. The variables are forecasted from period 0, when the market is in a steady state.
2. The central bank creates a monetary shock 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.[39] This way, it will be possible to assess whether a particular permanent shock to the level of nominal aggregate demand, interacting with the two different types of productivity shocks expected to arrive while the monetary shock dies away, is expected to have a permanent effect on the level of real aggregate output. If a permanent effect is anticipated, then LRMN fails in the model.

[35] A smaller value of λ increases the kurtosis of the idiosyncratic shock distribution and, thereby, that of the distribution of nonzero price changes as well.

[36] It would seem realistic to assume that positive productivity shocks are likelier to arrive than negative ones; their distribution is still assumed to be symmetric around zero. This assumption serves convenience only; it facilitates comparison with DSGE-type menu cost models but can be relaxed in the future. Note that supply potentials are still likelier to increase in the model than to decrease because their aggregate component is assumed to exhibit trend growth.

[37] The within-firm correlation of goods-specific productivity shocks is restricted from being equal to 1 as the resulting ratio's denominator in Equation (6) would be 0.

[38] Section 5 and Section 6 will clarify that many different steady state distributions exist under demand–supply interactions.

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

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

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

Note: The test equations include an intercept and a deterministic time trend. The optimal lag length is selected according to the Schwarz information criterion. * - significance at $p < 0.10$, ** - significance at $p < 0.05$, *** - significance at $p < 0.01$.

4.5. Estimating the strength of demand–supply interactions

A key parameter determining the long-run real effects of monetary shocks in the model is η, the strength of demand–supply interactions. This subsection is therefore devoted to establishing a simple empirical estimate for its value.

To estimate the parameters of Equation (4), it seems necessary to have empirical estimates about the aggregate component of supply potentials. However, as shown in Online Appendix C, it is sufficient to have estimates about macro-level potential output if the law of large numbers can be assumed to hold for idiosyncratic productivity shocks, that is, if they cancel out in the aggregates.[40] Under this assumption, the potential growth rate always equals the growth rate of the aggregate component of supply potentials and, hence, $\log g_t^{\mu}$ can be substituted with $\Delta\ \log\overline{Q}_t$, the growth rate of potential output, when estimating Equation (4).

Quarterly data about real GDP and quarterly estimates of the potential GDP in the U.S. are used 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. Estimates from the U.S. Congressional Budget Office are used to measure potential output.[41] As the two empirical distributions characterizing micro-level price adjustment are based on a dataset 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, quadratic spline interpolation is used to approximate the possible monthly time series of real GDP and potential GDP. The estimates of η are based on this interpolated sample covering all the months between January 1989 and December 1997 (108 observations altogether), which is the same period during which the Dominick's dataset was collected. A larger sample is used as a robustness check, containing interpolated monthly data 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 $\widehat{Q}_t$.

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. Surprisingly, the null hypotheses that the time series of the potential growth rate and output gap contain unit roots cannot be rejected based on the 1989–1997 sample. However, they can be rejected at the 5% significance level based on the full (1949–2018) sample, suggesting that the two variables are stationary; however, the period between 1989 and 1997 is probably too short to reveal their stationarity. Hence, Equation (4) can probably be estimated using the 1989–1997 sample, but it will also be estimated using the 1949–2018 sample 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	$\Delta\ \log\overline{Q}_t$		
η	0.0192*** (0.0013)	0.0183*** (0.0011)	0.0566*** (0.0068)
σ_{ν}	0.0002	0.0007	0.0006
Constant	Yes	Yes	Yes
Sample	1989–1997	1949–2018	1989–1997
Frequency	Monthly	Monthly	Quarterly
R^2	0.68	0.26	0.68
Number of observations	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 three different samples. A constant term is included in the equation in all cases, but its value is not reported, as $\overline{g}^{\mu}$ will be calibrated later to match the empirical value of the mean nonzero price change, allowing the model to generate a realistic rate of trend inflation.[42] The estimations have been performed with ordinary least squares (OLS). The estimate for η seems to be quite robust; it is around 0.02 in both the 1989–1997 sample and the 1949–2018 sample. It is significantly different from zero at all reasonable levels of significance. 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.

A natural argument 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. To assess the validity of this counterargument, Equation (4) is re-estimated using the original quarterly sample, which does not contain interpolated observations. η remains significantly different from zero at all reasonable significance levels.

The estimated 0.02 value of parameter η is in accordance with its few existing estimates. DeLong and Summers (2012) came up with several rough estimates for the value of η, which must be around 0.24 according to their conclusion based on annual data. The estimate of $\eta \approx 0.02$ is based on monthly data; thus, it corresponds to an annual estimate of $\eta \approx 12 \times 0.02 = 0.24$ roughly, which is the same value as the one estimated by DeLong and Summers (2012). Jorda et al. (2020) also estimated an equation similar to Equation (4) with the growth rate of TFP as the left-hand-side variable. Using annual data, they concluded that the 95% confidence interval of η is $[0.21,\ 0.30]$. The estimates presented in Table 2 fall into this range once they are transformed to annual frequency.

The estimate for the standard deviation of aggregate productivity shocks seems to be robust, as well. σ_{ν} is not greater than 0.0007 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%.[43]

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

[41] The time series are downloaded from the FRED database of the Federal Reserve Bank of St. Louis.

[42] A lower steady-state potential growth rate accelerates trend inflation for a given steady-state growth rate of nominal aggregate demand.

[43] However, this value may be underestimated because of the use of interpolated time series that are less volatile than the true ones.

4.6. Calibration

Based on the results of *Subsection* 4.5, the value of η is set to 0.02 in the model, while the value of σ_ν will be 0.0002. Some further parameters have values assigned 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 tolerable from the perspective of the computational burden. Specifically, T is set to 10,000, and the number of different product varieties $N \times G$ is set to 1000. It is assumed that $G = 2$, which is the same as the value used by Midrigan (2011) and Karádi and Reiff (2019). Two different goods per firm are sufficient 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 at the value of 1000.

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

The nominal GDP measures nominal aggregate demand, and its monthly time series is approximated from the quarterly series using quadratic spline interpolation. The data are sourced from the U.S. Bureau of Economic Analysis,[44] and are seasonally adjusted. The value of the steady-state gross growth rate of nominal aggregate demand $\bar{g}^Y$ is set to 1.0046, the average gross monthly growth rate of nominal GDP in the U.S. between 1989 and 1997. The two other parameters of stochastic process (2) governing nominal aggregate demand are estimated by fitting an AR(1) process on the monthly growth rate of the U.S. nominal GDP. The persistence of nominal demand growth φ is estimated to be 0.61, and the standard deviation of monetary shocks σ_ξ is estimated at 0.0015. These are almost the same values as those estimated by Midrigan (2011) using the monthly time series of monetary aggregate M1 to measure nominal aggregate demand.[45]

There is no consensus in the literature regarding the value of parameter ρ that determines the persistence of the goods-specific component of supply potentials. Following Costain and Nakov (2011) and Karádi and Reiff (2012), its value is set to 0.95, leading to highly persistent goods-specific components.

The rest of the parameters are calibrated to allow the model to match the most important moments of the two empirical distributions related to micro-level price adjustment.[46] The standard method of calibrating DSGE-type menu cost models is the simulated method of moments (SMM); this is also the easiest way to estimate the parameters of agent-based models (Grazzini and Richiardi, 2015; Fagiolo et al., 2019). For these reasons, the remaining model parameters are estimated using SMM. According to the central idea of SMM, the estimated combination of parameters minimizes the average distance between some moments simulated by the model and their empirical counterparts.[47] In particular, the unweighted sum of squared log deviations between the moments' simulated and empirical values is used as a criterion function to be minimized.[48] The number of moments used for calibrating the model is the same as the number of estimated parameters, ensuring that the model is just identified.

Table 3
The values of the parameters.

Notation	Parameter	Value
Assigned parameter values		
T	Length of a simulation	10,000
N	Number of firms	500
G	Number of goods supplied by the same firm	2
ε	Across-firm elasticity of substitution	3
γ	Across-good elasticity of substitution	1.1
$\bar{g}^Y$	Steady-state gross nominal growth rate	1.0046
φ	Persistence of monetary shocks	0.61
σ_ξ	Standard deviation of monetary shocks	0.0015
η	Strength of demand–supply interactions	0.02
σ_ν	Standard deviation of aggregate productivity shocks	0.0002
ρ	Persistence of idiosyncratic productivity shocks	0.95
Calibrated parameter values		
α^U	Strength of upward price adjustment	0.477
α^D	Strength of downward price adjustment	0.581
$\bar{z}$	Mean price adjustment threshold	0.119
σ_z	Standard deviation of price adjustment thresholds	0.050
θ	Asymmetry of price adjustment	0.344
$\bar{g}^\mu$	Steady-state gross potential growth rate	1.0038
σ_ζ	Standard deviation of idiosyncratic productivity shocks	0.066
λ	Probability of a nonzero idiosyncratic productivity shock	0.045
ρ_ζ	Within-firm correlation of goods-specific productivity shocks	0.553

Table 3 contains the parameter values. The parameter values that were calibrated during the SMM estimation are reported separately from those assigned before the estimation. According to the estimates, the values of the parameters determining the strength of price adjustment have intermediate magnitudes. The strength of upward price adjustment α^U is smaller than the strength of downward price adjustment α^D (0.477 versus 0.581). This is not surprising as the model reproduces EO7, which states that the average price increase is smaller than the average price decrease. These values indicate that, conditional on price adjustment, a 1% positive (negative) difference between anticipated demand for a good and its supply potential induces a 0.477% (0.581%) price increase (decrease). The mean price adjustment threshold $\bar{z}$ is 11.9%, meaning that for the average firm, the weighted average difference between anticipated demand for its products and their supply potentials must exceed 11.9% to induce price adjustment. 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 34.4% smaller than the weight assigned to products with anticipated excess demand, when firms are considering whether to change their prices. In a steady state, the potential output grows by 0.38% from month to month, as $\bar{g}^\mu$ 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 found in the literature.[49] The probability λ of a nonzero idiosyncratic productivity shock arriving is 0.045, which is again close to the standard values reported in the menu cost literature.[50] Finally, the within-firm correlation, ρ_ζ, between goods-specific productivity shocks is 0.553, which is between the value produced by Midrigan's (2011) model (0.53) and the value assumed by Karádi and Reiff (2019) (0.60).

Table 4 can be used to assess the model's goodness of fit by comparing the values of moments in the empirical and the simulated data; the values of moments that have been targeted during the SMM estimation are underlined. The model can almost perfectly match all the targeted

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

[45] The value of φ is the same, but his estimate for σ_ξ (0.0018) is slightly greater than 0.0015. A possible reason for this is that this paper uses an interpolated monthly time series, which is less volatile than the true one. Karádi and Reiff (2019) also used the same values as Midrigan (2011).

[46] The values and the relevance of these moments are described in Section 3.

[47] See Adda and Cooper (2003) for a didactic description about the simulated method of moments.

[48] In the case of moments, which are allowed to be negative, the log deviations between their simulated and their empirical values are substituted with their relative deviations.

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

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

Table 4
The values of targeted and non-targeted moments in the empirical data and the data simulated by the model.

Moment	Data	Model
Distribution of nonzero price changes		
Mean (%)	1.9	1.9
Mean size (%)	9.7	9.8
Standard deviation (% points)	12.5	12.4
Kurtosis	4.28	4.29
Ratio of the mean sizes of price increases and decreases (%)	81.8	81.3
Fraction of price increases (%)	66.0	64.7
Fraction of small price changes (%)	28.9	29.1
1st decile (%)	2.1	2.1
1st quartile (%)	3.9	4.4
Median (%)	7.2	7.6
3rd quartile (%)	12.0	13.0
9th decile (%)	22.3	20.3
Frequency distribution of price changes		
Mean (%)	11.6	11.6
Standard deviation (% points)	5.4	5.3
Skewness	0.62	0.62
1st decile (%)	5.1	5.1
1st quartile (%)	7.4	7.4
Median (%)	11.1	11.3
3rd quartile (%)	14.7	14.9
9th decile (%)	19.2	17.9
An additional moment		
Mean year-on-year inflation rate (%)	2.60	1.59

Note: The moments targeted during the SMM estimation are underlined. The fraction of small price changes is the fraction of price changes smaller than half of the mean size of nonzero price changes. In the case of the distribution of nonzero price changes, the quantiles refer to the 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 measured by the GDP-deflator.

moments of the two empirical distributions. Some of the most important quantiles of the two distributions are also reported in Table 4. These have not been targeted during the SMM estimation. However, the model can still match them satisfactorily, indicating that it can reproduce the whole shapes of the empirical distributions sufficiently well, not just some of their moments targeted during the estimation. The mean year-on-year inflation rate is 1.59% in the model, which is around 1 percentage point below the mean annual inflation rate in the U.S. between 1989 and 1997, measured to be 2.60% by the GDP-deflator. However, this is not necessarily a model deficiency as the rate of trend inflation inherent in the Dominick's dataset is possibly different from the general rate of trend inflation in the U.S. during the period when the dataset was collected.[51] Nevertheless, the model's 1.59% trend inflation rate can be regarded as a realistic magnitude. In summation, the model's empirical fit can be considered satisfactory; hence, it is suited to determine estimates about the long-run real effects of monetary shocks in the U.S. during a normal period, such as between 1989 and 1997.

5. The long-run real effect of a typical monetary shock

In this section, the hybrid menu cost model presented in Section 4 is used to estimate the long-run real effect of a typical positive monetary shock in the U.S. during normal times. The *growth rate* of nominal aggregate demand is hit with a *transitory* shock, which leads to a *permanent* increase in its *level*. Then, it is observed if there are any forces in the model that are expected to lead real aggregate output back to its initial steady-state value in the long run. If there are such forces, LRMN holds. If there are no such forces, LRMNN occurs.

Fig. 2 presents the impulse responses of the most important aggregate variables to a typical, one standard deviation positive monetary shock. Inflation on the figure is denoted by *P*%. LRMN fails in the model as the real aggregate output is not expected to return to its initial level as the monetary shock dies away. Instead, it settles into a permanently higher-level steady-state growth path. 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 a 0.39% permanent shock to its level. When the path of nominal aggregate demand reaches 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 price level path is expected to converge to a new steady-state level 0.30% above the baseline. The 0.09% long-run real effect is significantly different from 0% as 79.22% of the 10,000 trajectories, the average of which approximates the impulse response function of real aggregate output, is above 0% 300 periods, that is, 25 years after the arrival of the shock.[52] This fraction is significantly greater than 50%, at all reasonable levels of significance.[53]

The long-run effectiveness of the monetary shock is measured with its fraction, which is expected to pass through to real aggregate output in the long run. This fraction is termed the *long-run pass-through to output*. It can theoretically be calculated as the ratio of the value of the impulse response function of real aggregate output to that of nominal aggregate demand on an infinite horizon as follows:

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

where $LRPT^{Q}$ denotes the long-run pass-through to output, and IRF^{X}_{t} is the value of the impulse response function of variable X t periods after the period preceding the arrival of the shock. In practice, IRF^{X}_{∞} is approximated by IRF^{X}_{300} for any variable X.

In the case of the one standard deviation positive monetary shock, $LRPT^{Q}$ is equal to 0.2308, which means that 23.08% (around one-quarter) of a typical positive monetary shock is expected to pass through to real aggregate output in the long run. The remaining 76.92% (around three-quarters) is expected to be absorbed by the price level. This implies that the long-run real effects of monetary shocks must have been substantial in the U.S. between 1989 and 1997, suggesting that LRMNN is more than an interesting theoretical possibility; it has considerable practical importance for monetary policy.

Few econometric estimates can be found in the literature about the long-run real effects of monetary shocks. Using annual U.S. data from 1869 to 1975, Fisher and Seater (1993) estimated that a 1% permanent increase in the level of the money supply is expected to lead to a 0.5% permanent increase in real GDP. Atesoglu (2001) estimated a cointegrating vector between money supply and real income using annual U.S. data from 1875 to 1998 and found that the long-run coefficient of the money supply is around 0.5. Both estimates suggest that $LRPT^{Q}$ must be around 50% empirically, implying that the hybrid menu cost model

[51] The trend inflation rate of typical goods sold in grocery stores between 1989 and 1997 could have been lower than the general rate of trend inflation in the U.S. Unfortunately, the large number of missing values makes it impossible to calculate the trend inflation rate inherent in the Dominick's dataset. An alternative would be to calculate the mean annual growth rate of the producer price index of grocery stores. However, the earliest year that the U.S. Bureau of Labor Statistics reports this price index for, is 2003, which is outside the Dominick's dataset's collection period.

[52] Three-hundred periods are sufficient for the model to get close enough to a steady state after the arrival of a monetary shock. Three-hundred periods correspond to 300 months, that is, 25 years in the model.

[53] A z-test was performed for the null hypothesis that the fraction of trajectories above 0% 300 periods after the arrival of the shock is equal to 50% against the one-sided alternative that it is greater than 50%. The p-value turned out to be smaller than 0.0001.

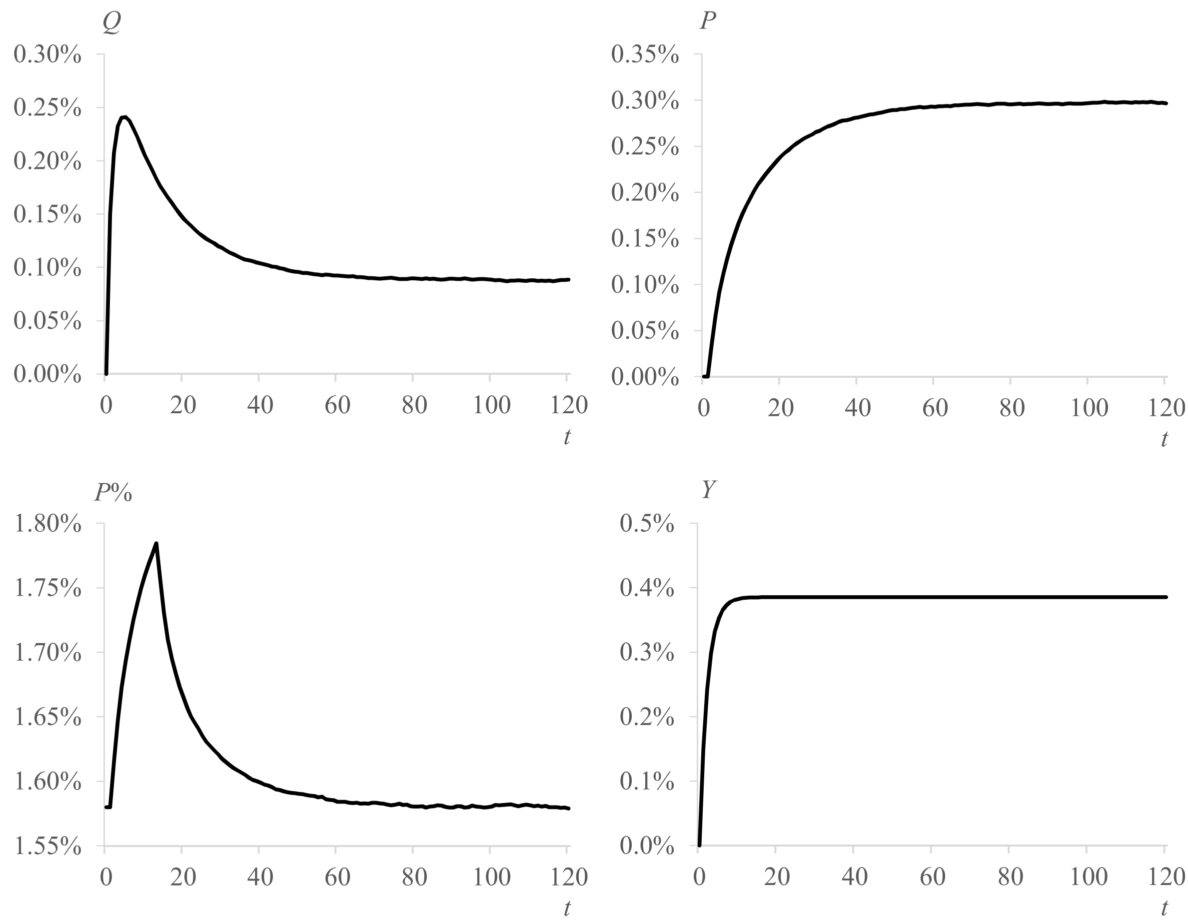

Fig. 2. The impulse responses of real aggregate output, the price level, and inflation to a one standard deviation positive permanent shock to the level of nominal aggregate demand.
Note: The notations are the following. Q: real aggregate output, P: price level, $P\%$: inflation rate, Y: nominal aggregate demand, t: period index. A period in the model corresponds to one month.

underestimates the long-run real effects of monetary shocks, compared to the two cited empirical studies. However, because of the endogeneity of cointegrated variables, the elements of a cointegrating vector cannot be interpreted as estimates of causal effects (Enders, 2015). De Grauwe and Costa Storti (2004) carried out a meta-analysis and estimated that a 1 percentage point increase in the nominal interest rate is expected to decrease real output by 0.16% in the long run. Jorda et al. (2020) estimated a much larger long-run real effect, to the same 1 percentage point increase in the nominal interest rate, equal to a 4.68% drop in real output in the long run.[54] These estimates are difficult to compare with the one produced by the hybrid menu cost model as this paper follows the usual methodology applied in the menu cost literature and does not explicitly model the interest rate decisions of the central bank.

6. Inspecting the mechanisms

In this section, the hybrid nature of the menu cost model is exploited to determine the roles that nonlinear price adjustment and demand–supply interactions play in the emergence of LRMNN. By turning the post-Keynesian and ACE features of the model on and off, it can be made clear how they influence the behavior of an otherwise standard menu cost model. Some simplified model variants will be studied, with some features turned on and some turned off. The parameters of these simple model variants are again estimated with SMM. Their values and the simulated values of the moments of the two distributions related to micro-level price adjustment can be found in Online Appendix D.[55]

All features that have been introduced just to improve the model's fit to the empirical data, are turned off. The resulting variants of the model will make it possible to focus on the roles played by nonlinear price adjustment and demand–supply interactions purely in the emergence of LRMNN. Further model features, which may also influence the emergence of LRMNN, will be introduced step by step. Specifically, all the model's simple variants share the following simplifying assumptions:

- Firms are assumed to be homogenous concerning their price adjustment thresholds ($\sigma_z = 0$), implying equally frequent price changes for all products.
- Single-product firms are assumed instead of multiproduct ones ($G = 1$)[56], that is, each firm supplies a single product variety.

[54] This estimate is obtained using their full sample containing annual data about 17 countries from 1890 to 2015. The same long-run real effect is estimated to be 2.98% in their post-war subsample.

[55] None of the simple model variants is sophisticated enough to reproduce all important empirical observations about micro-level price adjustment reported in Section 3. However, this section focuses on the qualitative implications of the model variants regarding LRMNN and not on their quantitative predictions; hence, it is not crucial to achieve satisfying goodness of fit.

[56] Note that the total number of product varieties sold in the market is kept at $N \times G = 1000$; hence, decreasing G from 2 to 1 requires increasing N from 500 to 1000.

- Trend growth is assumed away from nominal aggregate demand ($\overline{g}^Y = 1$) and, hence, trend inflation disappears. In the absence of trend inflation, there is no reason for firms to give asymmetric responses to positive and negative monetary shocks and, thus, price adjustment becomes symmetric ($\theta = 0$ and $\alpha^U = \alpha^D$).
- Potential growth, that is, trend growth in the aggregate component of supply potentials, is assumed away ($\overline{g}^\mu = 1$).
- Aggregate productivity shocks are assumed away ($\sigma_\nu = 0$) and, hence, idiosyncratic productivity shocks remain the only sources of variation in the supply potentials.
- The probability distribution of idiosyncratic productivity shocks is assumed to be normal instead of leptokurtic ($\lambda = 1$), that is, a normally distributed shock arrives in each period instead of arriving infrequently.

The starting point of the analysis is the benchmark model variant, labeled BM (Benchmark), which, does not contain any of the two features believed to generate LRMNN by post-Keynesian economists. This is based on three further simplifying assumptions: firms are not hit by idiosyncratic productivity shocks ($\sigma_\zeta = 0$) and, as such, supply potentials are constant; there are no demand–supply interactions ($\eta = 0$); and price adjustment is free, there are no menu costs to pay. The latter implies that the price adjustment threshold is zero for all firms ($z_i = 0$ for $\forall i$). Under these assumptions, firms become homogeneous; they all set the same price, and demand function (1) simplifies to $c_t = Y_t/Np_t$ for all product varieties. If firms were perfectly rational, they would recognize this and set the price to $p_t = Y_t/N\overline{q}$. This would perfectly coordinate demand with the supply potentials, and each firm would always produce a constant $\overline{q}$ amount of output.[57] Thus, under perfect rationality and no price rigidity, monetary shocks would fully pass through to the price level; they would have no real effects in the short or long run.

However, firms are boundedly rational in the model; they make their pricing decisions according to heuristic rule (3). The impulse response of the benchmark model variant to a two-standard deviation monetary shock is presented in Fig. 3.[58] The monetary shock has a small short-run real effect as boundedly rational firms cannot optimally react to the shock in the short run, resulting in too weak price adjustment and little real adjustment. In the long run, firms learn to adapt to the monetary shock by increasing their prices in response to the excess demand, neutralizing the shock's real effect. It can be concluded that the simple form of bounded rationality manifested in pricing decision rule (3) cannot explain LRMNN in the model, but it results in some small short-run real effects in response to monetary shocks.

6.1. Nonlinear price adjustment

Now, the nonlinearity of price adjustment is examined to determine whether it can explain the failure of LRMN in the model. Nonlinear price adjustment is turned on in the benchmark model variant, that is, positive price adjustment thresholds are assumed ($\overline{z} > 0$). The resulting model variant is labeled BM + NLPA, and its impulse response to a two-standard deviation monetary shock is presented in Fig. 3.

Nonlinear price adjustment leads to the failure of LRMN in model variant BM + NLPA. In the first few periods, nominal demand growth fully transforms into real output growth as firms do not adjust their prices in response to small deviations between demand and the supply potential. However, when their deviation grows large enough, firms become willing to pay the menu cost and increase prices. Real output falls as a consequence but immediately starts rising again as nominal aggregate demand increases further. This time, real demand does not get far enough from the supply potential to encourage firms to pay the menu cost. Hence, prices do not increase anymore, and real aggregate demand remains permanently higher when nominal aggregate demand settles to its new, higher steady-state level. Consequently, the quantities of all product varieties become permanently higher in the new steady state, implying that LRMN fails.[59]

So far, it seems that nonlinear price adjustment can explain LRMN's failure in the model consistently with the post-Keynesian view, but the question remains as to why LRMNN does not arise in DSGE-type menu cost models. A possible reason is that firms are assumed to be perfectly rational within their framework, and they decide their prices by solving a dynamic profit maximization problem. In Fig. 3, the quantities produced deviate permanently from the supply potentials in the new steady state of model variant BM + NLPA, causing infinitely large losses for firms in the long run, compared to the maximal attainable profit stream under flexible prices. A forward-looking firm may notice this and be willing to pay the finite menu cost in the present to avoid infinitely large expected future losses. Thus, it may revert the price to its flexible-price steady-state level, eliminating LRMNN.

A version of model variant BM + NLPA, containing dynamically optimizing firms, was built to assess the validity of this argument. It is labeled BM + NLPA + DynOpt. In this model variant, firms maximize their values, that is, the present value of their expected profit streams on an infinite horizon. Profits are assumed to depend negatively on the squared relative difference between actual output and the supply potential. In the case of price adjustment, they are decreased by the menu cost as well.[60] Firms choose between changing and maintaining prices by comparing their expected values in the two cases. Their dynamic profit maximization problem is solved numerically, using value function iteration. The technical details can be found in Online Appendix E.

Fig. 3 clarifies that despite the preliminary expectations, the assumption of dynamically optimizing firms does *not* eliminate LRMNN from model variant BM + NLPA. The explanation is that firms discount their expected future streams of profits during their pricing decisions. After discounting, the present value of the infinitely large expected losses caused by the lack of perfect price adjustment becomes finite. Hence, if the difference between the actual output and the supply potential is not too large, it is not optimal to pay the finite menu cost in the present to avoid expected losses in the distant future that may not even be realized at all. This means that the assumption of dynamically optimizing firms cannot be the reason why LRMN holds in DSGE-type menu cost models.

Another possible explanation for the prevalence of LRMN in DSGE-type menu cost models is the assumption that idiosyncratic productivity shocks hit the firms. Model variant BM + NLPA + IID extends model variant BM + NLPA with such shocks ($\sigma_\zeta > 0$).[61] It can be seen in Fig. 3 that the introduction of idiosyncratic productivity shocks eliminates LRMNN from model variant BM + NLPA. Firms are expected to be hit by

[57] Profits would be maximal if the output was equal to the supply potential, interpreted in Subsection 4.3 as the amount of output, which is the most cost-efficient to produce. Total revenues are $p_t q_t = p_t(Y_t/Np_t) = Y_t/N$, which is independent of firm decisions. In this case, profits are maximal if the firm produces at the lowest possible cost level.

[58] Under the calibration presented in Online Appendix D, a one standard deviation shock would not be large enough to induce firms in model variants BM + NLPA and BM + NLPA + DynOpt to change their prices. This section focuses on the qualitative implications of the simple model variants and not on their quantitative predictions.

[59] One might argue that the discrete jumps observable in the impulse response functions may be realistic at the micro-level but not at the macro level of the economy. The working version of this paper (Váry, 2020) shows that the impulse response functions become continuous if firms are assumed to be heterogeneous concerning their price adjustment thresholds as they start adjusting their prices to the monetary shock in different periods. LRMN fails under heterogeneous price adjustment thresholds, as well.

[60] The assumed shape of the profit function can again be motivated by the fact that revenues will eventually be independent of firm decisions under the assumption of homogeneous firms, and production is assumed to be the most cost-efficient at the supply potential.

[61] Firms are boundedly rational again in model variant BM + NLPA + IID.

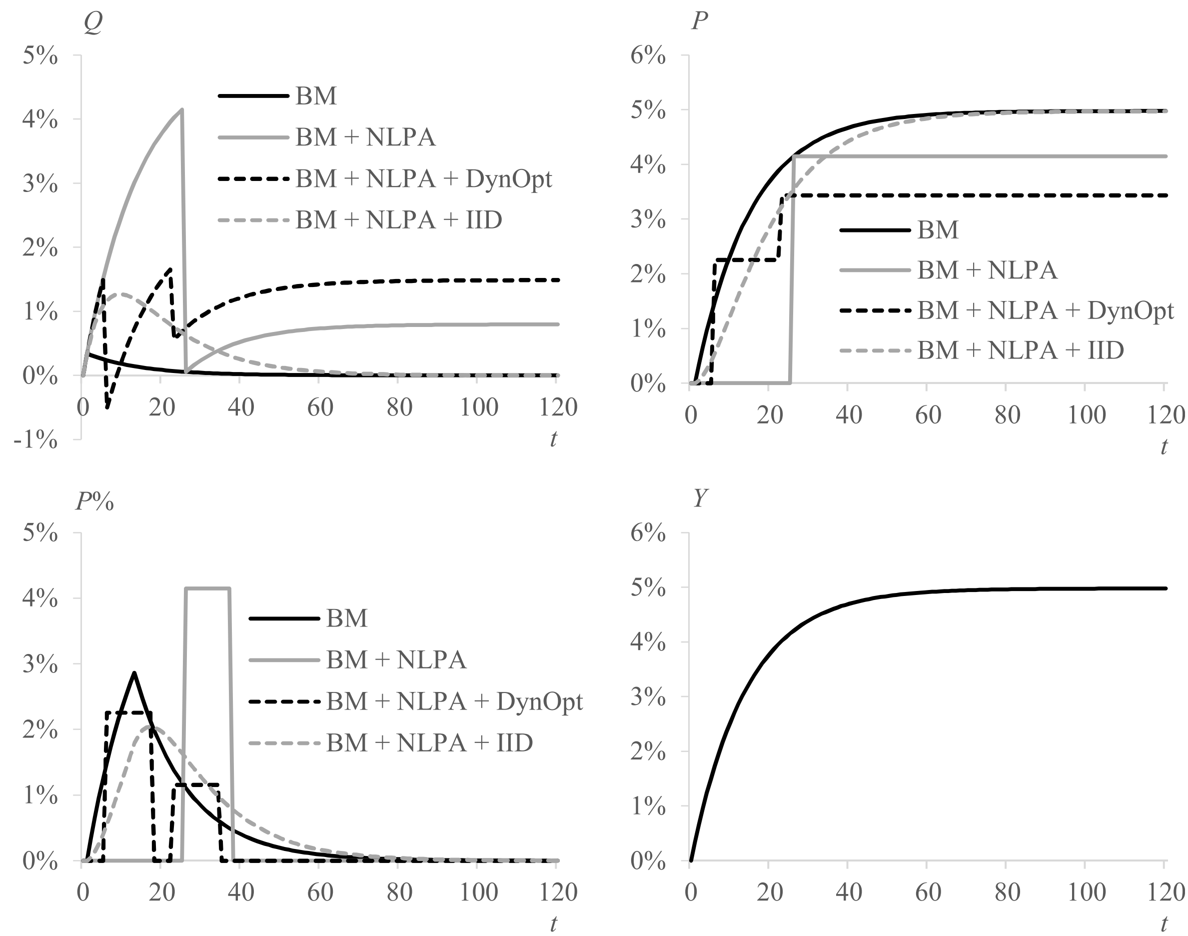

Fig. 3. The impulse responses of real aggregate output, the price level and inflation to a two standard deviation positive permanent shock to the level of nominal aggregate demand in the benchmark model variant and in model variants BM + NLPA, BM + NLPA + DynOpt and BM + NLPA + IID.
Note: The notations are the following. *Q*: real aggregate output, *P*: price level, *P*%: inflation rate, *Y*: nominal aggregate demand, *t*: period index. A period corresponds to a month. BM refers to the benchmark model variant that contains boundedly rational firms, linear price adjustment, and no demand–supply interactions. BM + NLPA is the benchmark model variant with nonlinear price adjustment. BM + NLPA + DynOpt is the benchmark model variant with nonlinear price adjustment and dynamically optimizing firms. BM + NLPA + IID is the benchmark model variant with nonlinear price adjustment and idiosyncratic productivity shocks.

micro-level productivity shocks as the monetary shock dies away. Sooner or later, each firm is expected to face an idiosyncratic shock that is large enough to push its supply potential sufficiently far from anticipated demand to induce price adjustment. If the firm adjusts its price because of the idiosyncratic shock, it will also respond to the monetary shock. Thus, idiosyncratic productivity shocks are expected to result in perfect price adjustment in the long run, reverting real output to its initial steady-state value. This result clarifies that the reason why nonlinear price adjustment does not lead to LRMNN in DSGE-type menu cost models is that the menu cost assumption is complemented with the assumption that idiosyncratic productivity shocks hit the firms.

Idiosyncratic productivity shocks need to be key ingredients of an empirically relevant menu cost model; they are necessary to make the model able to reproduce the large mean size of empirical price changes (Golosov and Lucas, 2007) and the overall shape of the empirical distribution of nonzero price changes (Midrigan, 2011). Table D2 in Online Appendix D illustrates that the simple model variants without idiosyncratic productivity shocks cannot reproduce the large mean size of empirical price changes. The importance of idiosyncratic productivity shocks is stressed by numerous empirical studies as well, according to which most of the variation observed in firm- or plant-level productivity is because of idiosyncratic factors (Bergoeing et al., 2003; Ábrahám and White, 2006; Bachmann and Bayer, 2013; Castro et al., 2015). Thus, it can be concluded that the first post-Keynesian explanation for the failure of LRMN, which is a type of nonlinear price adjustment involving the existence of a price adjustment threshold, can lead to LRMNN in some simple theoretical models. Still, these models do not seem to be supported by the empirical data.[62] The full-fledged variant of the menu cost model presented in Section 4 contains idiosyncratic productivity shocks. Hence, the type of nonlinear price adjustment that involves the existence of a price adjustment threshold cannot be the reason it produces significant long-run real effects in response to monetary shocks.

6.2. *Demand–supply interactions*

Next, the paper examines if demand–supply interactions alone can explain the failure of LRMN in the model. In a case of perfect rationality and no price rigidity, demand–supply interactions cannot occur as the output gap is always zero. Hence, they cannot induce any changes in potential output. Therefore, the starting point of the analysis is the same benchmark model variant as the one already presented, which contains boundedly rational firms, linear price adjustment, and no demand–supply interactions. It has been established that LRMN holds in this model

[62] Of course, it is theoretically possible to find a new assumption to replace the arrival of idiosyncratic productivity shocks in assuring satisfying empirical performance for a menu cost model, which does not eliminate LRMNN generated by nonlinear price adjustment. However, it is not a trivial task to find such an assumption; hence, it is out of the scope of this research.

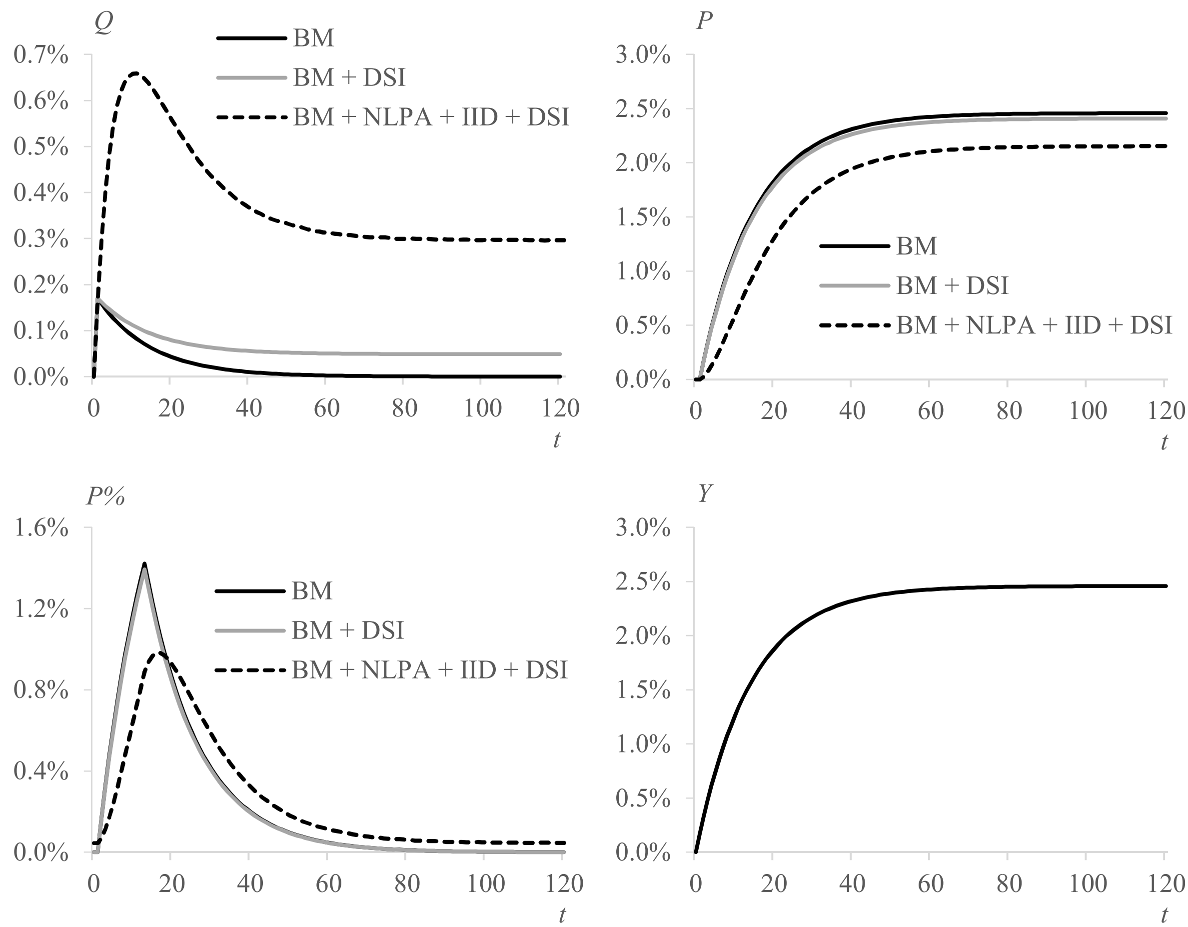

Fig. 4. The impulse responses of real aggregate output, the price level and inflation to a one standard deviation positive permanent shock to the level of nominal aggregate demand in the benchmark model variant and in model variants BM + DSI and BM + NLPA + IID + DSI.
Note: The notations are the following. *Q*: real aggregate output, *P*: price level, *P%*: inflation rate, *Y*: nominal aggregate demand, *t*: period index. A period corresponds to a month. BM refers to the benchmark model variant that contains boundedly rational firms, linear price adjustment, and no demand–supply interactions. BM + DSI is the benchmark model variant with demand–supply interactions. BM + NLPA + IID + DSI is the benchmark model variant with nonlinear price adjustment, idiosyncratic productivity shocks, and demand–supply interactions.

variant.

Demand–supply interactions are turned on in the benchmark model variant ($\eta > 0$), and the resulting model variant is labeled BM + DSI. Its impulse response to a one standard deviation monetary shock is presented in Fig. 4. Demand–supply interactions lead to the failure of LRMN in model variant BM + DSI. The bounded rationality of pricing decisions results in a small short-run real effect in response to the monetary shock, generating a positive output gap, which increases potential output through the mechanisms of demand–supply interactions. As nominal aggregate demand approaches its new steady-state level, firms gradually raise their prices in response to the excess demand. The unfolding process of price adjustment increases the price level, reducing real aggregate demand and output. However, firms adjust to higher supply potentials than those prevalent before the arrival of the monetary shock, the result of which is that real aggregate output remains permanently higher when nominal aggregate demand settles down at its new, higher steady-state level. Thus, LRMN fails.

Nonlinear price adjustment is necessary for the model to reproduce the most important moments of the empirical frequency distribution of price changes, and idiosyncratic productivity shocks are necessary to reproduce those of the empirical distribution of nonzero price changes. Model variant BM + NLPA + IID + DSI augments model variant BM + DSI with these two features ($\overline{z} > 0$ and $\sigma_\zeta > 0$). Its impulse response, presented in Fig. 4, shows that LRMN fails within its framework, as well. Unlike the long-run real effects of monetary shocks generated by nonlinear price adjustment, idiosyncratic productivity shocks do not eliminate LRMNN generated by demand–supply interactions. Thus, it can be concluded that the presence of demand–supply interactions as the second post-Keynesian explanation for the failure of LRMN can generate LRMNN in an empirically relevant way. This is why monetary shocks have long-run real effects in the full-fledged variant of the hybrid menu cost model presented in Section 4.

However, it is worth noting that in Fig. 4, the long-run real effect of a monetary shock is much larger if demand–supply interactions are coupled with nonlinear price adjustment. This is because price rigidity generates a much larger short-run real effect in response to the shock than the bounded rationality of pricing decisions alone. In other words, demand–supply interactions transform larger short-run real effects into correspondingly larger long-run real effects. Despite the inability of nonlinear price adjustment to generate long-run real effects in response to monetary shocks in an empirically relevant way, it plays an important role in determining their *magnitude* once they are brought to life by demand–supply interactions.

The key role of demand–supply interactions in the emergence of LRMNN raises the question of how sensitive the long-run real effect of a typical monetary shock is to their strength. Online Appendix F shows that the long-run effectiveness of such a shock is substantially influenced by the strength of demand–supply interactions in the full-fledged variant of the hybrid menu cost model. However, the standard error of the estimated strength of demand–supply interactions in Table 2 is only 0.0013,

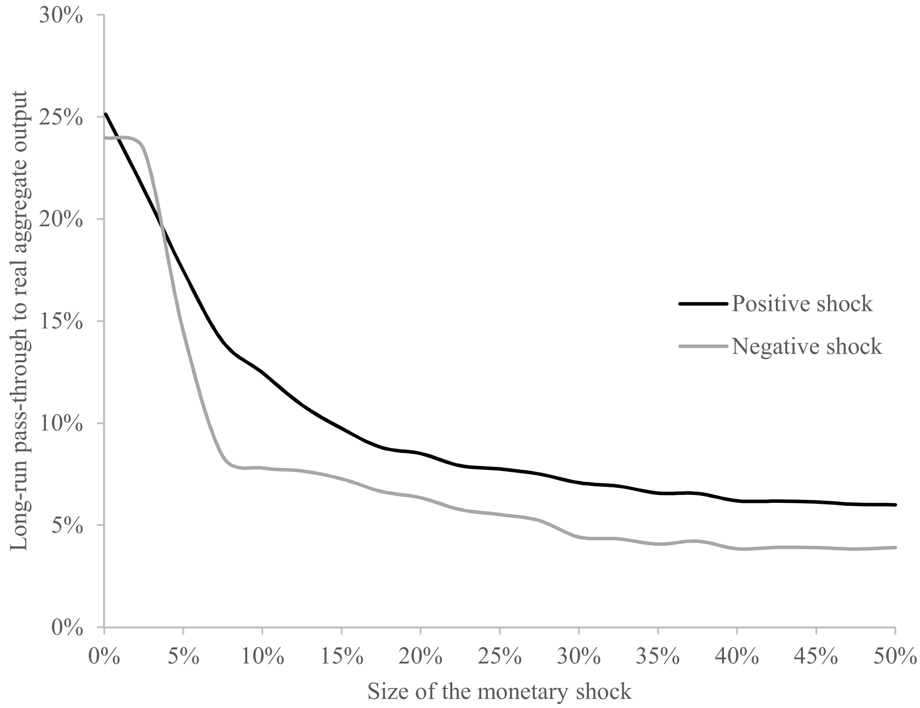

Fig. 5. The long-run effectiveness of a monetary shock in the model as a function of its size in cases of positive and negative shocks.

implying a rather narrow ± 2 standard error confidence band for the value of parameter η: $(0.018, 0.021)$. If η were assumed to be equal to the lower bound of this confidence band, the model would predict that 21.97% of a typical monetary shock would pass through to real output in the long run, which is only slightly below the 23.08% long-run pass-through predicted under the baseline parameterization of $\eta = 0.02$. Hence, even under a conservative assumption about the strength of demand–supply interactions, the long-run effectiveness of a typical monetary shock is estimated to be substantial.

7. The effect of the size and the sign of a monetary shock on its long-run effectiveness

This section returns to the full-fledged variant of the hybrid menu cost model presented in Section 4 to discover how the size and the sign of a monetary shock influence its long-run effectiveness.

7.1. The effect of the shock size on the long-run effectiveness of a monetary shock

Section 5 presents the result regarding the substantial long-real effect of a typical positive monetary shock. The finding seemingly indicates a simple secret to successful monetary policy: central banks need to hit the economy with an infinitely large positive monetary shock, and real output will rocket to infinity. This subsection shows that pursuing such a monetary policy is unwise, even if LRMN does not hold.

Fig. 5 presents the long-run effectiveness of a monetary shock in the model as a function of its size, separately for positive and negative shocks.[63] The long-run effectiveness of a shock is measured by its long-run pass-through to output. First, only the case of positive shocks is considered. It is apparent that the larger the monetary shock, the smaller its fraction 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. At the same time, the fraction of the shock passed through to the price level in the long run increases. Thus, the long-run real effects of large monetary expansions are probably too small to compensate for their inflationary effects, implying that it is not rational for central banks to target unlimited increases in real output.

It is useful to turn to a well-known finding from the existing literature (Klenow and Kryvtsov, 2008; Costain and Nakov, 2011; Karádi and Reiff, 2012) to determine the reasons behind the decreasing effectiveness of long-run expansionary monetary policy as a function of the shock size. The extant literature shows that the short-run pass-through of a monetary shock to the price level can be decomposed into three components as follows:

1. *Intensive margin*: Desired price changes become larger as a consequence of the monetary shock.
2. *Extensive margin*: The fraction of firms adjusting their prices increases because of the monetary shock.
3. *Selection effect*: The monetary shock alters the composition of price adjusters. Firms with larger than average desired price changes turn into price adjusters with a higher probability.

In the model, price adjustment is stronger in the long run if it is stronger in the short run because according to Equation (4), the long-run real effects of monetary shocks to potential output are determined by their short-run real effects on the output gap. Hence, the three components of short-run price adjustment are important determinants of the strength of long-run price adjustment as well. Karádi and Reiff (2012) showed that the fraction of a monetary shock passed through to the price level because of price adjustment on the intensive margin stays constant as the shock size increases. However, the role of the extensive margin in macro-level price adjustment increases nonlinearly as the size of the shock becomes larger. The strength of the selection effect depends crucially on the assumed probability distribution of idiosyncratic

[63] As mentioned in Subsection 4.4, 10,000 independent replications were typically simulated with different random draws for the productivity shocks to approximate the impulse response functions. For creating Fig. 5, only 1000 independent replications were simulated to save computer time.

productivity shocks.[64]

In the context of the hybrid menu cost model, this means that the reason why the long-run effectiveness of a monetary shock decreases with its size is that more firms adjust their prices in the short run in response to larger shocks. Consequently, their short-run effectiveness becomes lower. Hence, demand–supply interactions will lead to lower long-run effectiveness.

It is worth noting that in Fig. 5, although the long-run effectiveness of a monetary shock decreases with the shock size, it remains slightly positive even for very large shocks.[65] This is initially surprising because practically all firms react to very large monetary shocks by adjusting their prices in the short run, that is, price adjustment is perfect on the extensive margin. However, it is not perfect on the intensive margin because of the firms' boundedly rational pricing decisions. This opens the way for small short-run real effects to emerge even in response to very large monetary shocks. When demand–supply interactions take place, small short-run real effects transform into small long-run real effects.

7.2. 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 in the short run than negative ones (DeLong and Summers, 1988; Cover, 1992; Morgan, 1993).[66] This subsection examines if this asymmetry can also be observed in the hybrid menu cost model between their *long-run* effectiveness.

The long-run pass-through to output in cases of positive and negative monetary shocks can be compared in Fig. 5 for different shock sizes. There is an intermediate range of the shock size, within which negative monetary shocks are more effective in the long run than positive ones; however, positive shocks are more effective outside of this range. The intermediate range of the shock size is roughly between 1% and 4%.[67]

The asymmetric results can be explained as follows. Karádi and Reiff (2012) showed that the role of the extensive margin in price adjustment to small monetary shocks is negligible. Hence, for small shock sizes, the intensive margin dominates price adjustment. However, price adjustment on the intensive margin is stronger in response to negative shocks than to positive ones. This is because the strength of downward price adjustment α^D is calibrated to be greater than the strength of upward price adjustment α^U to allow the model to reproduce EO7, according to which the mean size of price decreases is empirically larger than that of price increases. Consequently, the short-run real effects of small positive shocks will be larger than those of small negative ones. This asymmetry survives after the short-run real effects transform into long-run real effects through demand–supply interactions.

As the size of the monetary shock increases, the extensive margin begins to play an increasingly important role in price adjustment; however, the shock size at which it becomes dominant is larger in the case of negative shocks than in that 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. However, suppose the size of a *negative* monetary shock starts increasing. In this case, firms wait first for trend inflation to deteriorate their relative prices, allowing them to save on the menu cost of price adjustment.[68] This leads to the emergence of the intermediate range of the shock size, within which macro-level price adjustment to negative monetary shocks is weaker than to positive ones; hence, the real effects of negative shocks become larger.

Above a sufficiently large shock size, price adjustment on the extensive margin becomes practically perfect for both positive and negative shocks. In such situations, the difference between their real effects is determined by the intensive margin again. Hence, positive monetary shocks again become more effective than negative ones.

The results indicate that small positive monetary shocks are more effective than negative ones, which is not in line with the empirical evidence cited above.[69] However, price adjustment must be calibrated stronger downward than upward to allow the model to reproduce the empirically observable difference between the mean size of price increases and decreases. Nevertheless, more research needs to be done to reconcile these model predictions with the empirical evidence. An interesting possibility is to consider the nonlinearity of price adjustment during the empirical study of the asymmetric real effects.[70]

8. Concluding remarks

This paper studied whether heterogeneous micro-level price adjustment to monetary shocks, coupled with two economic mechanisms believed to explain LRMNN by post-Keynesian economists, leads to economically significant long-run real effects at the macro level. The positive results were based on a hybrid menu cost model that combines insights from DSGE-type menu cost models with ideas from post-Keynesian monetary macroeconomics, and the behavior of which was studied via agent-based simulations. The model was calibrated to match the most important moments of two empirical distributions related to micro-level price adjustment.

The long-run real effect of a typical monetary shock was estimated to be substantial, with around one-quarter of the shock passing through to real aggregate output in the long run. It turned out that demand–supply interactions are the key post-Keynesian mechanisms responsible for the emergence of LRMNN in the model. Nonlinear price adjustment, interpreted to be equivalent to the existence of a price adjustment threshold, is the other economic mechanism believed to lead to LRMNN by post-Keynesians; however, it was unable to explain the failure of LRMN in the model under empirically relevant conditions. Still, it was shown to fundamentally influence the magnitude of the long-run real effects of monetary shocks once they are brought to life by demand–supply interactions. The long-run effectiveness of a monetary shock was shown to decrease with its size, suggesting that it is not rational for central banks to target an unlimited increase in real output, even if LRMN fails. Finally, the long-run effectiveness of positive and negative monetary shocks is asymmetric in the model, under the assumed pricing decision rule allowing for different strengths of price adjustment in response to positive and negative shocks. Within an intermediate range of the shock size, the long-run effectiveness of negative shocks in the model is larger than that of positive ones, while positive shocks are more effective outside of this range.

[64] If their distribution is leptokurtic, as in the model, the selection effect is weak for small shock sizes; its importance increases substantially for medium-sized shocks and starts decreasing again for large shock sizes.

[65] 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.

[66] See Florio (2004) for a survey about the potential explanations of this empirical finding.

[67] Considering that the standard deviation of monetary shocks is estimated to be 0.15%, the size of a shock is not very likely to fall into this range but it is not impossible. According to the results of Karádi and Reiff (2019), the changes in the Hungarian VAT rate in 2006 can be considered to be equivalent to monetary shocks with sizes falling into the intermediate range under some simple assumptions.

[68] This is a standard result of menu cost models with trend inflation (Ball and Mankiw, 1994; Karádi and Reiff, 2019).

[69] 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.

[70] Another possibility is to assume in the model that demand–supply interactions are stronger in cases of negative demand shocks than in those of positive ones. This assumption would be in line with some empirical evidence (Ball, 2009) and would help the model produce larger *long-run* real effects in response to small negative monetary shocks, but it would not lead to different predictions concerning the asymmetry of *short-run* real effects.

The results have important implications for the conduct of monetary policy. If the long-run real effects of monetary shocks are substantial, then there is no divine coincidence and strict inflation targeting cannot be the optimal monetary policy. Central banks should put more emphasis on real economic activity during their policy decisions than under LRMN. It is suggested that they follow the flexible opportunistic approach of inflation targeting put forward by Fontana and Palacio-Vera (2007) and target additional real variables besides the output gap (Galí, 2020; Garga and Singh, 2021). The results also serve as arguments in favor of the policy of price-level targeting (Svensson, 1999; Gaspar et al., 2010; Evans, 2012; Bernanke, 2019).

There are three major ways of continuing the research. First, more empirical work should be done to understand the channels of demand–supply interactions and the monetary transmission mechanism through which the long-run real effects of monetary shocks are manifested. This would contribute to producing a better-founded econometric estimate regarding the strength of demand–supply interactions and, thereby, the long-run real effects of monetary shocks. It would also help support demand–supply interactions with proper microeconomic foundations, making it possible to develop policy recommendations about influencing the long-run real effects of monetary shocks.

Second, it would be very useful to study this paper's research questions within the framework of a complex agent-based macro model. The hybrid menu cost model presented in this paper only contains the goods market of an economy. DSGE-type menu cost models contain a stylized labor market and a bond market, but their roles in determining the real effects of monetary shocks are negligible. An agent-based macro model would make it possible to develop detailed microeconomic foundations for demand–supply interactions, thereby to understand which segments of the economy, unrelated to goods market pricing behavior directly, determine the long-run real effects of monetary shocks.

Third, this paper did not consider the possible role of any demand-side mechanism in generating LRMNN. However, money illusion, which prevents households from fully adjusting their reservation wages to changes in the price level, can also result in a long-run trade-off between inflation and real economic activity (Akerlof et al., 2000). It would be interesting to study how strongly money illusion amplifies the long-run real effects of monetary shocks found in this paper.

Nevertheless, the results presented in this paper provide useful foundations for future research for at least two reasons. First, they point out that the key for the emergence of substantial long-run real effects in response to monetary shocks is the *existence* of demand–supply interactions, and their exact forms are of secondary importance. Second, ACE macro models are often criticized for being *black boxes*; they are often too complex to easily clarify the economic mechanisms behind their novel implications. As the structure of the hybrid menu cost model in this paper mimics DSGE-type menu cost models, it was possible to clarify the roles of its post-Keynesian and agent-based features in determining the long-run real effects of monetary shocks. Thus, the model sheds light on the economic mechanisms needed to be key ingredients of a complex agent-based macro model for studying the long-run real effects of monetary shocks. Because of the findings arrived at with the hybrid menu cost model, it will also be easier to interpret the results from the agent-based macro model.

Declaration of competing interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Online Appendix A. Supplementary material

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