Bank of Finland Research Discussion Papers
16 • 2023

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Bank of Finland
Research

Bank of Finland Research Discussion Papers
Editor-in-Chief Esa Jokivuolle

Bank of Finland Research Discussion Papers 16/2023
26 October 2023

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ISBN 978-952-323-451-2, online
ISSN 1456-6184, online

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# Demographic Aging and the New Keynesian Phillips Curve

Gene Ambrocio*

**Abstract**

I document a link between old-age dependency ratios and average markups. I propose that a mechanism whereby households develop deep habits in consumption as they age could explain this feature of the data. I show that when this mechanism is embedded in an overlapping generations New Keynesian model, the slope of the New Keynesian Phillips Curve flattens as the population ages. Further, the contractionary effects of positive monetary policy surprises on output are amplified. Evidence from local projections exploiting the *Trilemma* in international macroeconomics confirm the model predictions. These results suggest that the challenges faced by monetary policy may become more pronounced as populations age.

*JEL Codes*: D11, E21, E32, E52, J11

*Keywords:* population aging, Phillips curve, deep habits, market power, markups

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Demographic aging poses a significant challenge for many economies. Several countries, notably Japan and many countries in Europe, already have more than a fifth of the population aged 65 and over and this is only expected to grow larger. Consequently, many studies have looked into the economic implications of aging focusing primarily on savings and wealth, rates of return on assets, and labor markets.[1] However, aging could also have implications on firm market power through changes in aggregate consumption behavior.

In this paper, I provide evidence supporting the plausibility of this channel and draw out the implications for the conduct of monetary policy. First, I document a new stylized fact, average markups are positively correlated with an aging population particularly in developed countries. This correlation is not attributable to common trends, broad structural changes (e.g., the shift towards services), or other potentially confounding factors. Using instrumental variable regressions, I strengthen the causal interpretation of this finding. The results indicate that the average increase in the share of the old from 1980 to 2016 could potentially account for about 16-38% of the increase in average markups for the 40 countries in my sample over the same period.

One explanation for this stylized fact is that households gradually develop habits and start caring more about the non-price features of a product and less about its relative price as they age.[2] Consistent with this notion, I use European household survey data to show that older households tend to care more about non-price characteristics when making food purchases. It is reasonable to think that people slowly develop tastes and preferences for a specific brand or product as they get older. This hypothesis is not altogether new. Parks and Barten (1973) speculated as much several decades ago as an explanation for why they found that OECD countries with older populations tended to be more price inelastic.

The hypothesis is also consistent with other findings in the literature.[3] As

[1] See e.g., Krueger and Ludwig (2007); Ferrero (2010); Carvalho et al. (2016); Aksoy et al. (2019); Rachel and Summers (2019); Gagnon et al. (2021); Auclert et al. (2021); Acemoglu and Restrepo (2022); Jones (2023); Maestas et al. (2023) and Karahan et al. (2024) among others.

[2] Indeed, several studies have attributed part of the observed increase in markups to declining price sensitivities of households (Brand, 2021; Atalay et al., 2023; Doepper et al., 2024).

[3] See e.g., Gafarov et al. (2023) who use detailed price and household expenditure data in the United States over the period 2001-2020 to show that declining price elasticities at the market-

households age, they accumulate brand loyalty and are less likely to try out other (and new) brands (Bornstein, 2021). Across households, these preferences would vary and give rise to a phenomenon referred to as *niche consumption* described in Neiman and Vavra (2023) whereby individual households would consume a few brands or varieties but households in the aggregate consume a diverse variety of products. *Niche consumption* appears to be more prevalent among older households relative to the young.[4] In turn, the accumulation of *brand capital* within households would allow firms to charge more for the products that they sell. Therefore, as households age, firms are able to charge higher markups.

Motivated by these features in the data, I develop a model of age-dependent deep habits drawing on Ravn et al. (2006). I embed deep habits formation in the basic New Keynesian framework augmented with Blanchard-Yaari overlapping generations.[5] Deep habits at the differentiated goods level critically affects the ability of monopolistic competitive firms to extract markups from sales. Further, when deep habits are formed over households' lifetimes, the age distribution becomes an important determinant to aggregate deep habits and thus the shape of demand curves that firms face.

The model predicts that aging-induced increases in average deep habits results in higher market power by firms. In turn, and with Rotemberg price adjustment costs, we also get a flattening of the New Keynesian Phillips Curve. This is because, an increase in aggregate deep habits makes firms more reluctant to change prices (and thus their market share) in response to shocks today. Moreover, monetary tightening becomes more contractionary and the contraction is more persistent as populations age, worsening the inflation-output tradeoff faced by monetary policy.[6] To support this prediction of the model, I provide

good-year level plays an important role in the trend increase in markups as well as Curtis et al. (2024) who use a similarly detailed dataset over the period 2004-2019 to show that older US households have lower price elasticities.

[4]See Figure 3 in Neiman and Vavra (2023).

[5]See e.g., Ravn et al. (2010); Lubik and Teo (2014); Zubairy (2014); Leith et al. (2015) for other examples of New Keynesian models with deep habits.

[6]The output cost due to disinflation used in this paper is calculated with respect to a temporary reduction in inflation, e.g., when the monetary authority has deemed it to be currently too high, and not a permanent reduction in the inflation rate (target).

evidence from state-dependent local projections on the response of output to a monetary policy surprise using the *Trilemma* identification approach of Jorda et al. (2020).

I do not claim that demographic aging is the primary driver of observed changes to markups charged by firms or the slope of the New Keynesian Phillips Curve. De Loecker and Eeckhout (2020) (and De Loecker et al., 2020) show that the increase in average markups across countries over the last few decades has largely been driven by the right tail of the markup distribution and that reallocation of market share from low- to high-markup firms plays an important role.[7] Nevertheless, Doepper et al. (2024) among others point out that markups have also increased within product categories. As such, the mechanism that I highlight provides a complementary explanation linking firm market power also to demographic aging.

Demographic aging could also affect average markups through a consumption basket recomposition channel. Cravino et al. (2022) link aging with a reallocation of production towards service-related products. In turn, Mangiante (2024) shows that these sectors also tend to have higher degrees of price rigidity such that the sectoral shift towards services could also result in a flattening of the New Keynesian Phillips Curve. However, the evidence in the literature documenting increases in markups also at the product level as well as the evidence I provide indicate that sectoral reallocation does not present a complete picture of the link between aging and markups. Specifically, the relationship between aging and markups that I find in the data controls for structural changes involving the share of services, size of government, financial development, labor market conditions, and trade.

Closest to the mechanism I propose is found in Curtis et al. (2024) who directly assume that older households have lower price elasticities for which

[7] De Loecker et al. (2021) identify productivity and market structure as key factors in the increase of markups while Liu et al. (2022) propose a low-interest rate environment as conducive to increasing market concentration and market power. De Ridder (2024) link the rise in market power to intangibles wherein an increase in intangible inputs lowers marginal costs but raises fixed costs deterring entry. On a related note, Koh et al. (2020) link the rise in (capitalization of) intangible intellectual property to declining labor shares in the United States. See also the rise of *superstar* firms who charge higher markups in Autor et al. (2020).

they also find supporting evidence from US micro-data. On the other hand, my mechanism relies on deep habits that develop over households' lifetimes which is meant to capture the increasing importance of familiarity with a product and a preference for non-price features when making consumption choices as a household grows older. A key distinction is that aging-induced changes in aggregate deep habits do not alter the slope of the marginal cost New Keynesian Phillips Curve while changes in price elasticities do. Consequently, in my model, demographic aging flattens the slope of the output New Keynesian Phillips Curve while the slope of the marginal cost curve remains unchanged. This aligns with Gagliardone et al. (2023) who find that the marginal cost curve remains steep and that it is the link between marginal cost and output which has weakened.

The mechanism I propose also differs from the model of *niche consumption* in Neiman and Vavra (2023). Markups are unchanged in Neiman and Vavra (2023) as competitive forces from an increase in the number of aggregate varieties consumed cancel out the additional market power that firms get as households concentrate more on consuming their preferred varieties. On the other hand, monopolistic competitive firms in my model take full advantage of increasing deep habits as households age leading to an increase in markups.[8] In this regard, my mechanism is closer to *consumer inertia* described in Bornstein (2021). While Bornstein (2021) focuses on the implications of the aging-induced increase in consumer inertia on the formation of new firms and business dynamism, I focus on the implications of aging-induced increase in habits on the pricing decision of firms and its implications for monetary policy.

To keep the model parsimonious and the effects of the proposed channel transparent, the model I propose abstracts from these other mechanisms in the literature and focuses solely on the effects of aging on firm pricing behavior when firms are identical.[9] Instead, the model incorporates two layers of pro-

[8] In contrast, Feenstra et al. (2022) are able to link consumer preference heterogeneity with market power in that they assume non-negligible fractions of consumer groups have similar preferences that differ across groups.

[9] That is, I abstract from shifting preferences towards sectors which may have differing degrees of price rigidities and market power as well as firm entry and exit. See also Roldan-Blanco and Gilbukh (2021) who model the dynamic problem of firms in attracting and retaining its customer base. In their model as sellers' customer base grow larger, they extract more rents, i.e., charge higher markups.

duction with monopolistic competition between the two layers. Changes in the parameter capturing the degree of market power between the two layers of production represents all other forces that would change average markups. In this regard, my mechanism and the model's predictions represent only a specific aspect through which demographic aging contributes to jointly explaining the trend increase in markups and the trend decline in the slope of the New Keynesian Phillips Curve.

My results complement the broader literature linking demographics, inflation, and monetary policy. Recent studies have explored how aging impacts inflation and monetary policy largely through aging-induced changes to the natural rate of interest.[10] Juselius and Takats (2021) link demographic changes to low frequency variation in inflation. Katagiri et al. (2020) show that under the fiscal theory of the price level and when fiscal policies are determined via maximizing the welfare of current voters, an increase in life expectancy is deflationary while a fall in the birthrate is inflationary. Berg et al. (2021) find that the consumption of the elderly are more responsive to monetary policy shocks in the US. Leahy and Thapar (2022) argue that the age distribution materially affects entrepreneurial activity while Bornstein (2021) relates aging to the formation of new (and smaller) firms and hence the composition of firms who would respond differently to monetary policy.[11] I propose an aging-deep habits consumption mechanism as a new channel.

My results linking demographic aging with the flattening of the New Keynesian Phillips Curve adds to the literature examining whether the Phillips Curve has indeed flattened. Many have argued that the Phillips Curve has been flat for some time already (Blanchard, 2016; McLeay and Tenreyro, 2019; Del Negro et al., 2020; Stock and Watson, 2020; Barnichon and Mesters, 2021; Beaudry et al., 2024). For instance, Hazell et al. (2022) find that the slope of the US Phillips curve was small even as far back as the 1980s. In addition, Gagliardone et al. (2023) find that the slope of the marginal cost Phillips curve remains steep and that it is the link between output and marginal cost which has weakened.

[10]See e.g., Fujiwara and Teranishi (2008); Bullard et al. (2012); Goodhart and Pradhan (2020).

[11]See also Liang et al. (2018) and Aksoy et al. (2019).

The anchoring of inflation expectations is one of the more common reasons brought up to explain a flat(ter) Phillips Curve. Other explanations propose non-linearities and state dependencies in nominal rigidities or the tightness of labor markets as an explanation for why the slope may change over time (Ascari and Sbordone, 2014; Forbes et al., 2022; Costain et al., 2022; Gasteiger and Grimaud, 2023; Siena and Zago, 2024) while some also link the declining slope to other trends such as shifts in production networks (Hoeynck, 2020; Rubbo, 2023) or declining industry competition (Fujiwara and Matsuyama, 2022).[12] Closest to the channel I propose is the one suggested in Fujiwara and Matsuyama (2022) whereby a shift towards less market competition can account for both the observed increase in markups and decline in estimated slopes of the Phillips Curve. My contribution in this regard is to illustrate how demographic aging can induce a decline in market competition.

The next section provides some evidence on the statistical link between the age structure and markups and support for the notion that deep habits accumulate as a household ages. Section 2 introduces an Overlapping Generations New Keynesian model with Deep Habits to rationalize the observed relationship between demographic aging and average markups. Section 3 draws out the implications of demographic aging on the conduct of monetary policy. Section 4 tests the model predictions regarding the output-inflation trade-off of monetary policy. Finally, Section 5 concludes with some remarks.

# 1. Demographics and markups

I collect annual data on macroeconomic and socio-demographic indicators covering 40 countries over the period 1980 to 2016 from the World Bank World Development Indicators. These are matched to estimates of average markups from De Loecker and Eeckhout (2020). The sample consists of a mix of both OECD member and non-member countries. Descriptive statistics, the list of countries covered, and the sample coverage per country are reported in Ap-

[12] In relation to Siena and Zago (2024) who link job polarization to the slope of the Phillips Curve, Moreno-Galbis and Sopraseuth (2014) note that population aging can also contribute to job polarization due to differences in the consumption preferences of the elderly.

pendix tables A.1 and A.2. On average, life expectancy, the share of old-age dependents, and markups have grown over time while the share of the young and population growth have both declined. These are also generally more readily apparent for developed or OECD member countries in the sample.

## 1.1. *Empirical evidence on the relation between the age distribution and markups*

A univariate regression of markups on several demographic factors show a positive correlation between average markups and the age-dependency ratio, life expectancy, population growth, the fertility rate, and the share of female to total population.[13] These are, of course, simple correlations and very likely to be spurious. We have not accounted for potential common trends or cross-country factors that may generate these correlations. The demographics variables themselves are highly correlated with each other. To take into account these considerations, I regress markups on combinations of demographic factors as well as year and country fixed effects (standard errors clustered by country). In addition, several control variables are included in these regressions to capture differences in economic structure, financial development, and labor market characteristics. In particular, the list of control variables include real GDP, the ratios of the current account and total trade to GDP, government spending as a fraction of GDP, savings to GDP, and the share of services to GDP as factors relating to economic structure. Further, variables such as the labor force participation rate, the unemployment rate, and population density are used to control for labor market characteristics while the ratio of stock market capitalization to GDP and domestic credit to GDP are used to account for financial development. Table 1 reports results from these regressions.[14]

[13] See Table A.3 in the Appendix. I also find that net migration is not statistically correlated with average markups.

[14] It should be noted that in some specifications, lagged markups - an estimated variable - is included as a control which introduces a generated regressor problem. However, I also conduct Arellano-Bover-Blundell-Bond dynamic panel regressions as well as two stage least squares instrumental variable regressions with similar results as the baseline panel fixed effects regressions estimated by ordinary least squares.

Table 1: Multivariate regressions of markups on age dependency

| Dep. var.: Markups | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Age dependency ratio (total) | 0.009 | 0.009 | 0.006 | 0.004 | | |
| | (0.00) | (0.00) | (0.00) | (0.00) | | |
| Share young to total pop. | | | | | 0.014 | 0.008 |
| | | | | | (0.01) | (0.00) |
| Share old to total pop. | | | | | 0.017 | 0.015 |
| | | | | | (0.01) | (0.01) |
| Share female to total pop. | 0.024 | -0.144 | -0.089 | -0.057 | -0.095 | -0.071 |
| | (0.03) | (0.08) | (0.05) | (0.04) | (0.05) | (0.04) |
| L.Markups | | | 0.428 | 0.489 | 0.425 | 0.492 |
| | | | (0.19) | (0.12) | (0.19) | (0.12) |
| Additional controls | NO | YES | YES | YES | YES | YES |
| Fixed effects | Y,C | Y,C | Y,C | | Y,C | |
| Observations | 1356 | 628 | 628 | 628 | 628 | 628 |
| Adj. R-sq. | 0.584 | 0.758 | 0.805 | | 0.805 | |
| AR(1) p-value | | | | 0.000 | | 0.000 |
| AR(2) p-value | | | | 0.914 | | 0.884 |

*Cluster-robust standard errors (by country) and robust standard errors for the dynamic panel regressions are reported in parentheses. The table reports multivariate regressions of average markups on combinations of demographic factors and several control variables. Data is annual and covers the period 1980-2016 for 40 countries. For the Arellano-Bover-Blundell-Bond dynamic panel regressions, p-values from tests of residual serial correlation up to 2 lags are also reported. Control variables used, but not reported, are real GDP, the ratio of current account to GDP, the ratio of total trade to GDP, the ratio of government expenditures to GDP, the savings to GDP rate, the share of Services sector value-added to GDP, the labor force participation rate, the unemployment rate, population density, change in life expectancy, population growth, the ratio of stock market capitalization to GDP, and the ratio of domestic credit to GDP. Panel fixed effects regressions include year and country fixed effects.*

Column 1 of Table 1 reports results from a regression with only the demographics variables and country and year fixed effects while column 2 reports results once the additional control variables are included in the specification. I find that the age-dependency ratio and possibly the share of female to total population remain significantly correlated with average markups. I include lagged markups in the regression specifications reported in columns 3 and 4 using panel fixed effects and a dynamic panel regression respectively. In these regressions, the age-dependency ratio remains a statistically significant predictor of average markups. Finally, columns 5 and 6 report panel fixed effects and dynamic panel regression results when the age dependency ratio is split into the share of the young and old dependents. Here I find that both the share of the young and old dependents matter for the correlation between age-dependency and average markups. Using the coefficient estimates in columns 5 and 6, a 5.2% increase in the share of the old-age dependents (the average increase in the sample from 1980 to 2016) would raise markups by 0.08 to 0.09 which is between 16% to 18% of the average increase in markups in the sample over 1980 to 2016.

I repeat the regression exercise using sub-samples of the data. In particular, I split the sample across three periods and into OECD-member and non-member countries. Regression results are reported in Table 2. Columns 1 to 3 report results when the sample is split into three time periods, 1980-1992, 1993-2004, and 2004-2016 respectively. Columns 4 and 5 report results when I restrict the sample to OECD member and non-member countries respectively. I find that the coefficient on the share of young dependents is no longer statistically significant in any of the sub-samples. On the other hand, the coefficient on the share of old dependents remain statistically significant and positive for the latter two-thirds of the sample (covering 1992-2016) and for the OECD member country sub-sample. Using the coefficient estimates from column 4, an increase of the share of old-age dependents by 6.2% (the change in average shares for OECD countries from 1980 to 2016), would increase markups by 0.07 or about 10% of the increase in average markups in OECD countries from 1980 to 2016.

Table 2: Dynamic Panel Regressions: Sub-samples

| Dep. var.: Markups | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Sample | 80-92 | 92-04 | 05-16 | OECD | non-OECD |
| Share young to total pop. | -0.006 | 0.048 | 0.015 | 0.002 | 0.003 |
| | (0.02) | (0.03) | (0.01) | (0.00) | (0.01) |
| Share old to total pop. | 0.013 | 0.061 | 0.029 | 0.011 | -0.008 |
| | (0.05) | (0.04) | (0.01) | (0.01) | (0.02) |
| Share female to total pop. | -0.021 | 0.170 | -0.108 | -0.069 | 0.075 |
| | (0.19) | (0.25) | (0.05) | (0.04) | (0.05) |
| L.Markups | 0.238 | 0.180 | 0.581 | 0.814 | 0.397 |
| | (0.17) | (0.17) | (0.06) | (0.05) | (0.10) |
| Additional controls | YES | YES | YES | YES | YES |
| Observations | 158 | 374 | 452 | 591 | 393 |
| AR(1) p-value | 0.027 | 0.046 | 0.002 | 0.003 | 0.074 |
| AR(2) p-value | 0.316 | 0.131 | 0.797 | 0.358 | 0.129 |

*Robust standard errors are reported in parentheses. The table reports Arellano-Bover-Blundell-Bond dynamic panel regressions of average markups on combinations of demographic factors and several control variables. The p-values from tests of residual serial correlation up to 2 lags are also reported. Control variables used, but not reported, are real GDP, the ratio of current account to GDP, the ratio of total trade to GDP, the ratio of government expenditures to GDP, the savings to GDP rate, the share of Services sector value-added to GDP, the labor force participation rate, and population density.*

At this point, the results indicate that the old-age dependency ratio is the most consistent demographic predictor of average markups. I then verify whether this threshold (65 and over) is indeed the right one by running regression specifications which take into account the full age distribution of the population. I take the share of the population in five year age increments (e.g. 0-4, 5-9, 10-14, etc.) up to 80 years of age and older as the key explanatory variable. As these shares are highly persistent and correlated with each other, I use factor analysis to shrink the number of explanatory variables. Juselius and Takats (2021) make use of a similar approach to study the link between demographic changes and inflation.[15] I extract four factors from the 17 age groups and run regressions using the same controls as before. Regression results are reported in Table A.4 in the Appendix. The estimated effects confirm the basic finding. Specifically,

[15] In the Appendix, I also report regression results using the polynomial shrinkage approach adopted by Juselius and Takats (2021). See Table A.4.

the results indicate that the share of those aged in between their mid twenties and early fifties are associated with lowering average markups. Further, the results indicate a trend increase in the contribution to markups starting from the mid thirties rather than an abrupt change once a household reaches the old-age threshold of 65.

To strengthen the causal link between population aging and markups, I instrument the old-age dependency ratio with a plausibly (more) exogenous instrument - the share of those who were between 45 to 49 years old 20 years ago.[16] Given that the threshold age for the old-age dependency ratio is 65, those who were between 45 to 49 years of age 20 years ago would enter the old-age category today. Moreover, to strengthen the conditional exogeneity of the instrument I also include as additional control variables the share of those who were between 35 to 44 years old to total population 20 years ago. Those who were 35 to 44 years of age 20 years ago are not too different from those who where 45 to 49 years old and would go through the same experiences as those who were between 45 to 49 years of age over the next 20 years. However, this 35-44 age group cohort 20 years ago would still be below the 65 years of age threshold today.

The instrumental variable identification strategy relies on the restriction that conditional on the country and year fixed effects, the control variables capturing the structure of the economy today, and the additional control variables capturing the share of those who were 35-44 years of age 20 years ago, the share of those who were 45 to 49 years of age 20 years ago have no effect on average markups today except through the old-age dependency ratio (share of the population over 65 years of age) today. As alternative instruments, I also consider the share of those who were 55-59 years of age 10 years ago and the share of those who were 50-54 years of age 15 years ago. It is also important to note that the effects to be estimated are not associated with any specific cohort (e.g., the *baby boomer* generation) as each year in the regression sample is associated with a different cohort.

[16] A similar strategy is employed in Karahan et al. (2024) who instrument labor supply growth across US states with 20 year lags of birthrates.

The results of the two-stage least squares instrument variable regressions are reported in Table 3 along with OLS estimates for comparison.[17] The first four columns report results from OLS regressions using the baseline set of controls in the first column and with the additional controls associated with each of the instruments in the next three columns. Columns 5 and 6 report the second stage results when instrumenting the old-age dependency ratio with the share of 55-59 years of age 10 years ago without and with the share of 45-54 10 years ago as an additional control respectively. Columns 7 and 8 report the second stage results when the instrument is the share of those aged 50-54 years of age fifteen years ago and columns 9 and 10 report results when the instrument is the share of those aged 45-49 years of age twenty years ago.

Table 3: Instrument variable regressions of age dependency on markups

| Method | OLS | | | | TSLS | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Instrument | N.A. | | | | L10.Share 55 to 59 | | L15.Share 50 to 54 | | L20.Share 45 to 49 | |
| Dep. var.: Markups | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Share old to total pop. | 0.017 | 0.015 | 0.016 | 0.016 | 0.043 | 0.036 | 0.045 | 0.038 | 0.049 | 0.041 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.02) | (0.02) | (0.02) | (0.02) | (0.03) | (0.02) |
| Share young to total pop. | 0.014 | 0.017 | 0.016 | 0.016 | 0.019 | 0.022 | 0.019 | 0.022 | 0.020 | 0.022 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Share female to total pop. | -0.095 | -0.099 | -0.095 | -0.093 | -0.128 | -0.128 | -0.130 | -0.126 | -0.135 | -0.127 |
| | (0.05) | (0.05) | (0.05) | (0.05) | (0.06) | (0.06) | (0.06) | (0.06) | (0.06) | (0.06) |
| L.Markups | 0.425 | 0.414 | 0.416 | 0.415 | 0.418 | 0.409 | 0.417 | 0.411 | 0.416 | 0.408 |
| | (0.19) | (0.19) | (0.19) | (0.19) | (0.18) | (0.18) | (0.18) | (0.18) | (0.18) | (0.18) |
| L10.Share45to49 | | 0.003 | | | | 0.013 | | | | |
| | | (0.01) | | | | (0.02) | | | | |
| L10.Share50to54 | | 0.047 | | | | 0.038 | | | | |
| | | (0.02) | | | | (0.02) | | | | |
| L15.Share40to44 | | | -0.000 | | | | | 0.011 | | |
| | | | (0.01) | | | | | (0.02) | | |
| L15.Share45to49 | | | 0.040 | | | | | 0.033 | | |
| | | | (0.02) | | | | | (0.01) | | |
| L20.Share35to39 | | | | 0.000 | | | | | | 0.013 |
| | | | | (0.01) | | | | | | (0.02) |
| L20.Share40to44 | | | | 0.039 | | | | | | 0.034 |
| | | | | (0.02) | | | | | | (0.01) |
| Additional Controls | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Fixed Effects | Y,C | Y,C | Y,C | Y,C | Y,C | Y,C | Y,C | Y,C | Y,C | Y,C |
| Observations | 628 | 628 | 628 | 628 | 628 | 628 | 628 | 628 | 628 | 628 |
| Adj. R-sq. | 0.805 | 0.807 | 0.806 | 0.806 | 0.801 | 0.805 | 0.801 | 0.804 | 0.799 | 0.803 |
| First Stage F Stat. | | | | | 13.414 | 19.636 | 14.059 | 22.467 | 12.589 | 20.942 |

[17] To preserve the same sample coverage as the rest of the regression analyses, I collect data on the age distribution from the 1960s onwards to compensate for the up to 20 year lags in the instrument variable regression specifications.

*Cluster-robust standard errors (by country) are reported in parentheses. The table reports multivariate regressions of average markups on the old-age dependency ratio and several control variables. The first four column reports OLS estimates. The fifth to tenth columns report second stage instrument variable regression estimates instrumenting the old-age dependency ratio with the 10 year lag of the share of 55 to 59 years of age to total population (columns five and six), the 15 year lag of the share of 50 to 59 years of age to total population (columns seven and eight) and the 20 year lag of the share of 45 to49 years of age to total population. Data is annual and covers the period 1980-2016 for 40 countries. Additional control variables not reported are the change in life expectancy, population growth, real GDP, the ratio of current account to GDP, the ratio of total trade to GDP, the ratio of government expenditures to GDP, the savings to GDP rate, the share of Services sector value-added to GDP, the labor force participation rate, the unemployment rate, population density, real GDP per capita, the ratio of stock market capitalization to GDP, and the ratio of domestic credit to GDP. Country and year fixed effects are also included in all specifications. Instrument variable regressions also report the Kleibergen-Paap First stage F statistic.*

The results from the instrumental variable regressions support the basic finding, that the old-age dependency ratio is associated with higher average markups across countries and time. Consistent with the notion that adding the lagged shares of those who would be just under the 65 years of age threshold today as an additional control would sharpen the identification, the first stage F statistics are also larger when these controls are added to the specification. Averaging the estimates from columns 6, 8 and 10 of Table 3, a 5.2% increase in the share of the old (the average increase from 1980-2016 for the sample) would raise markups by 0.19 or about 38% of the actual average increase in markups in the sample over 1980-2016.[18]

## *1.2. Potential channels linking demographic aging and market power*

What might explain these findings? We can consider the two main economic activities of households, labor provision and consumption, which affects firms' costs of production and the demand that they face. With regard to the latter, one can further distinguish between changes in the composition of the consumption basket as a household ages and a general change in consumption behavior over lifetimes.

Regarding the provision of labor services, potential changes in the propensity to supply labor, the quality or efficiency of labor supplied, or one's market power when negotiating wages in the labor market may change as households age. Aging may also change the structure of the economy through related supply-side mechanisms. Boucekkine et al. (2002) provide a theory of

[18] Note that this would correspond to a local average treatment effect.

endogenous human capital accumulation to show that changes in both fertility and longevity could have medium and long-term consequences for growth. Feyrer (2007) provide evidence linking the age structure with aggregate productivity. Acemoglu and Restrepo (2022) link aging with increased automation in production. Another important aspect is with regard to aging and innovation or entrepreneurship. Liang et al. (2018); Aksoy et al. (2019); Bornstein (2021), and Leahy and Thapar (2022) show that the age distribution matters for innovation and entrepreneurial activity. These channels would imply that aging can reshape the firm distribution or the behavior of the average firm and consequently, the average markups that they charge.

At the same time, aggregate consumption behavior in terms of which types of goods are consumed may also change over households' lifetimes. For instance, Della Vigna and Pollet (2007) show that demographic changes generate predictable shifts in demand for specific sectors and consequently their profitability and stock returns. Regarding life cycle consumption baskets, Cravino et al. (2022) and Mangiante (2024) show, using household data from the United States, that services consumption increases as a households age while Banks et al. (2019) highlight medical-related expenditures as an important aspect to differences in old-age consumption between US and UK households. Aguiar and Hurst (2013) show that patterns in life-cycle non-durable consumption are driven by changes in the consumption of work-related or work-synergistic expenditures such as eating out at restaurants, clothing, and transportation. These changes in household consumption baskets would then translate into a recomposition in the production of goods and services which could then alter the average markups observed at the aggregate level.

The results reported in the previous section document the effects of the old-age dependency ratio on average markups after controlling for a broad set of indicators relating to general economic and financial development (e.g., real GDP, population growth, savings rate, credit to GDP), labor market conditions (e.g., unemployment and labor force participation rates), as well as the structure of the economy (e.g., total trade to GDP, government spending to GDP, and share of services to GDP). Consequently, the effects of demographic aging on labor markets and the supply-side structure of the economy in general are not the most likely channels generating the documented results. Instead, I focus on the potential effect of aging on firm market power through the way that it reshapes the demand curves that firms face which is expanded on in the next section.

### *1.3. Aging and deep habits in consumption*

Another dimension to the aging and consumption relationship may be that households' sensitivities to relative prices may decline as they get older. Doepper et al. (2024) use detailed micro data on prices and quantities in the US to show that the 30% increase in markups from 2006-2019 is likely partly due to a decrease in consumer price sensitivity over time.[19] Relatedly, Brand (2021) find that price elasticities have dropped by about 25% over 2006-2017. Changes in consumption baskets over time is ruled out as the documented relationship focuses on changes within product categories over time. Instead, one can consider older households as simply having lower price elasticities of demand. This is exactly what Curtis et al. (2024) find for US households over the period 2004-2019 using detailed micro-data on consumption and expenditures.

These recent findings echo results from much earlier studies. For instance, Pollak and Wales (1981) have shown decades ago using British household data that the age distribution matters for demand elasticities. Further, Parks and Barten (1973) use data from 1950 to 1967 and 14 OECD countries to show that increasing the proportion of dependents reduces price elasticities. This has led Parks and Barten (1973) to speculate that:

> Old people's spending patterns may be dominated by strong habit patterns that make them less sensitive to price changes. Teenagers may be affected by peer pressures that explain their insensitivity to prices when compared with working-age adults; however they seem to show higher sensitivity when compared with old people. (Parks and Barten, 1973, p. 849)

[19] See also Atalay et al. (2023).

While the above quote was made in reference to lower estimated price elasticities, it makes allusions to a specific mechanism, habits in consumption. This paper focuses on this hypothesis and explores its implications on firm price setting and the conduct of monetary policy. Rather than directly assuming that older households have lower price elasticities, I explore the possibility that households gradually develop preferences for specific products or brands due to their non-price characteristics as households gain consumption experience over time.

This approach has many advantages. For instance, Aguiar and Hurst (2007) find that because of a lower opportunity cost of time, older households spend more time shopping and end up paying lower prices for the same goods.[20] Nevertheless, they also find that older households tend to go to the same stores and consume the same brands and are, if anything, more brand loyal than younger households. This is corroborated by recent evidence in Bronnenberg et al. (2024) who use Dutch household micro-data to show that consumption has both a price and a time cost although they find that older households are also more willing to purchase more time-intensive and expensive goods.

The focus on deep habits and a growing preference for non-price characteristics as a household ages is also supported by other related findings in the literature. Notably, Bornstein (2021) finds that older households are more likely to continue consuming brands that they have consumed in the past and are less likely to try out new or other brands. Bronnenberg et al. (2012) have earlier shown that households' consumption is partly driven by *brand capital*.[21] A related finding by Neiman and Vavra (2023) is that the average household's spending is increasingly concentrated in a few products while households as a group are consuming a larger variety of products over time. They refer to this as *niche consumption*. While Neiman and Vavra (2023) focus mostly on trends over time, their results also indicate that older households exhibit stronger niche

[20]See also Aguiar and Hurst (2005) who find that older households substitute food expenditure with meal preparation time holding the quality and quantity of food consumption constant. A trend reduction in the time spent shopping reflecting an increase in the opportunity cost of time is also one of the explanations brought up in Doepper et al. (2024) to explain the fall in price sensitivity that they document.

[21]See also a review of the literature on brand capital and consumer brand loyalty in Bronnenberg and Dube (2017).

consumption behavior.

Finally, I find additional evidence consistent with this hypothesis using European household survey data taken from the Eurobarometer Survey conducted in 2012. The survey, with over 26 thousand respondents from 27 European countries, covered issues concerning food purchases among others. Specifically, respondents were asked how important several features such as the price, the quality, the geographic origin, and the brand of the product, are when making food purchases. After controlling for other factors such as education, occupation, financial conditions, and regional variation, I find that the importance of prices for food purchases is decreasing with age, particularly as one reaches the mid 50s in age, while non-price factors become more important. The results from these regressions are reported in Table 4.

The dependent variables are responses on the relative importance of several product features when making food purchases (decreasing scale). Columns 1 and 2 of Table 4 reports results with the importance of price as the dependent variable. The positive coefficients which tend to grow larger as households age indicate that older households place less importance on the price as a deciding factor for food purchases. On the other hand, the results from columns 3 to 8 where the dependent variables are now non-price characteristics such as quality, geographic origin and brand, I find the opposite pattern. Older households tend to care more about these non-price features relative to younger households.

Table 4: Importance of price and non-price features in food purchases

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Dep. var.: | PRICE | | QUALITY | | GEOGRAPHIC ORIGIN | | BRAND | |
| 25 - 34 years | 0.018 | 0.020 | -0.035 | -0.034 | -0.145 | -0.148 | -0.055 | -0.063 |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.03) | (0.03) | (0.03) | (0.03) |
| 35 - 44 years | 0.023 | 0.024 | -0.038 | -0.038 | -0.238 | -0.245 | -0.058 | -0.071 |
| | (0.02) | (0.03) | (0.02) | (0.02) | (0.04) | (0.04) | (0.04) | (0.03) |
| 45 - 54 years | 0.016 | 0.016 | -0.051 | -0.050 | -0.285 | -0.298 | -0.068 | -0.082 |
| | (0.03) | (0.03) | (0.02) | (0.02) | (0.04) | (0.04) | (0.05) | (0.04) |
| 55 - 64 years | 0.070 | 0.071 | -0.081 | -0.081 | -0.342 | -0.349 | -0.062 | -0.077 |
| | (0.03) | (0.03) | (0.02) | (0.02) | (0.05) | (0.04) | (0.06) | (0.04) |
| 65 years and older | 0.135 | 0.127 | -0.083 | -0.080 | -0.370 | -0.376 | -0.072 | -0.093 |
| | (0.04) | (0.04) | (0.03) | (0.03) | (0.06) | (0.05) | (0.07) | (0.05) |
| With children | -0.030 | -0.030 | 0.022 | 0.023 | 0.057 | 0.056 | 0.028 | 0.026 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.02) | (0.02) | (0.01) | (0.02) |
| Additional controls | YES | YES | YES | YES | YES | YES | YES | YES |
| Fixed effects | CNTRY | NUTS2 | CNTRY | NUTS2 | CNTRY | NUTS2 | CNTRY | NUTS2 |
| Adj. R-squared | 0.175 | 0.188 | 0.053 | 0.067 | 0.120 | 0.137 | 0.117 | 0.138 |
| Observations | 15977 | 15977 | 16092 | 16092 | 15946 | 15946 | 15759 | 15759 |

*Cluster-robust standard errors (by country or NUTS-2 regional classifications) in parentheses. The table reports multivariate regressions of the importance of several price and non-price features for food purchases on age and other factors. Note that the dependent variable is on a 4-point scale and coded such that 1 is very important and 4 is not at all important. Data is taken from the Eurobarometer Survey 77.2 conducted in 2012 with respondents from 27 European countries. Additional control variables are education, occupation, home ownership, reported difficulties in paying bills, marital status, gender, type of community, self-reported social status, internet use and ability, online purchases, and food logo awareness. All specifications include either country or NUTS-2 fixed effects.*

The results above take into account an array of households characteristics that may also drive food expenditure preferences. Specifically, I include variables which broadly control for income, wealth, financial conditions, education, employment, social status, and how well-informed the respondents are with respect to food products. These additional results, together with the related empirical findings in the literature, strongly suggest that preferences for specific product varieties - brands - also reflecting non-price features may develop and strengthen as households age. Consequently, less importance is placed on relative prices which would allow monopolistically competitive firms to charge higher markups. In the next section I formalize this hypothesis that the age distribution matters for deep habits in consumption and hence average markups. The next section describes a simple model which expands on the basic New Keynesian model with Deep Habits by incorporating a mechanism through which households develop deep habits as they age.

# 2. A model of age-dependent habits

This section presents an Overlapping Generations New Keynesian model with Deep Habits which links the age distribution to firm pricing behavior. The model draws on a key insight of deep habits that consumption habit persistence at the goods level effectively makes demand for differentiated goods less elastic (Ravn et al., 2006). It also brings expectations of changes in future demand into the current pricing problem of firms (Lubik and Teo, 2014). When augmented with a mechanism wherein habits develop as households age, the age distribution of the population begins to matter for the shape of demand curves faced by firms. In turn, it helps determine the markups that monopolistic competitive firms charge on the goods that they sell.

The objective of the model is to parsimoniously introduce age-specific deep-habits into a simple benchmark model with the minimum of ingredients to flesh out the implications on the New Keynesian Phillips Curve. The starting point is a simple version of the New Keynesian model with deep habits. I assume Blanchard-Yaari overlapping generations in order to generate an admittedly simplistic age distribution. To this setup, I add a key mechanism which is described in detail in the next section whereby households develop stronger deep habits as they age.

## *2.1. The formation of deep habits over lifetimes*

Consider a household born at time $t-J$ and denoted with $j$ who maximizes utility from consuming a basket of goods of unit length and indexed by $i$ representing the *sectors* of the economy.[22] The economy in which this household resides in produces a variety of products for each sector also of unit length and indexed by $k$. The whole product space is characterized by a unit square $\Omega$ with $i \in [0,1]$ sectors and $k \in [0,1]$ varieties per sector. Let $\Sigma_j \subset \Omega$ represent the set of products for which household $j$ has an inherent or latent preference for - meaning that consuming this subset of products is preferred by household $j$ relative to products not in this subset. Let $\Omega_i \subset \Omega$ denote the subset of all products

[22] There is a continuum of households $j \in J$ of a given age $J$.

in sector $i$ and $\Sigma_{j,i} = \Omega_i \cap \Sigma_j$ be the subset of preferred goods for a given sector $i$ by household $j$. For simplicity, assume that $\Sigma_{j,i}$ contains the same number of elements for each sector $i$ such that the set of preferred varieties in each sector is of equal length denoted by $s \in [0, 1]$. Consuming a variety from this preferred set has the unique property that the marginal utility is higher. Specifically let the marginal utility of consuming preferred and non-preferred varieties be given by,

$$\frac{\partial U_{j,t}}{\partial c_{i,k,t}} = \begin{cases} \bar{x}\left[c_{i,k,t} - \bar{c}\right]^{-1/\eta} & \text{if} \quad k \in \Sigma_j \\ \bar{x}\left[c_{i,k,t}\right]^{-1/\eta} & \text{if} \quad k \notin \Sigma_j \end{cases} \tag{1}$$

where $\bar{x} > 0$ and $\bar{c} > 0$ are some reference levels that will be more explicitly defined in subsequent sections.

Not all of the products are available to household $j$ for consumption in every period. Instead, when household $j$ enters the market for goods in period $t$ she randomly encounters a store offering a particular variety $k_{j,i,t}$ for each sector. The household can then consume either the variety offered or any variety previously encountered for each sector. That is, the household can choose to consume any variety in the set $\Omega_{j,t} = \Omega_{j,t-1} \cup \{k_{j,i,t}\}_{i=0}^{1}$.[23] If any of the preferred varieties is in this set, then the household consumes (randomly one of) that variety and if not, then the household (indifferently) consumes any one of the varieties in the set.

The likelihood that household $j$ encounters, and thus consumes, its preferred variety follows a geometric distribution over the number of times the household enters the market for goods or, equivalently, the household's age $J$. For any given period, the likelihood that the store *matched* to household $j$ offers a variety in her preferred set is given by $s$, the success parameter of a Bernoulli distribution. Consequently, the probability that a household encounters and consumes her preferred variety at age $J$ in time $t$ for sector $i$ ($\mathbf{1}_{i,j,t}$) is given by the cumulative distribution function of the geometric distribution, $1-(1-s)^J$.

$$Pr(\{k_{j,i,t'}\}_{t'=t-J}^{t} \cap \Sigma_{j,i} \neq \emptyset) \equiv \mathbb{E}[\mathbf{1}_{i,j,t}] = 1-(1-s)^J \tag{2}$$

[23]For completeness, $\Omega_{j,t} = \emptyset \quad \forall t < t-J$.

For simplicity, let $\Sigma_{j,i}$ also be randomly drawn across households and sectors such that the expected likelihood of consuming a preferred variety by one household at a given age is equal to the mass of households of that age consuming their preferred variety for each and all sectors.

The setup described above could be described as a random search (and matching) model with an ex-ante defined preferred set of varieties. It can nevertheless also be interpreted as a model where one develops preferences for or learns about their preferred consumption basket over their lifetime with repeated consumption experience. In this regard one can think of $s$ as the probability that a household wakes up one day and develops habits for consuming a good. This would be analogous to the concepts of the accumulation of *brand capital* (Bronnenberg et al., 2012), *consumer inertia* (Bornstein, 2021), or *niche consumption* (Neiman and Vavra, 2023). The intuition is simple. Everyone starts out as an uninformed beginner or novice with regard to consuming various goods. Initially, the most salient differentiator across brands and varieties would be the price. As one repeatedly consumes and gains familiarity with a particular product category, one begins to value and distinguish between the non-price features of a product. Therefore, as one ages, one is also less likely to let the price be the sole differentiating factor when making purchases. Consequently, one becomes more likely to be willing to pay more for these additional features.

In what follows, I embed this mechanism in an otherwise standard New Keynesian Deep Habits model that has been augmented to incorporate Blanchard-Yaari overlapping generations.

## 2.2. Households

Time is discrete and denote with $N_t$ the mass of households in the economy for period $t$ where $N_0 = 1$. At the beginning of every period a fraction $g^b$ of the mass of households in the previous period are born. At the end of each period a fraction $g^d$ of all household exit the economy such that the mass of households grow at the rate $g^b - g^d$ every period.

$$N_t = (1 + g^b - g^d)^t N_0 \tag{3}$$

Henceforth, all quantities will be expressed in per capita terms. Define $g \equiv g^b/(1+g^b-g^d)$, a summary statistic for the age distribution. Then the time-invariant age distribution $f(J)$ of households who have lived for $J$ periods is given by,

$$f(J) = g(1-g)^{J-1} \tag{4}$$

where $J \in [1\,,\infty]$. Households derive utility from consumption, provide labor services, and save in a one-period risk-free asset. They maximize the discounted sum of utility from consuming a basket of goods comprised of one variety, indexed by $k \in [0,1]$, for each sector $i \in [0,1]$ and the provision of labor services yielding the following program for a household $j$ born $J$ periods from today,

$$max \qquad \mathbb{E}_t \sum_{t'=0}^{\infty} \tilde{\beta}^{t'} U(\{c_{i,j,t+t'}\}, h_{j,t+t'}) \tag{5}$$

subject to:

$$U = \frac{x_{j,t}^{1-\sigma}}{1-\sigma} - \frac{h_{j,t}^{1+\kappa}}{1+\kappa} \tag{6}$$

$$x_{j,t} = \left[\int_0^1 (c_{i,j,t} - \theta_{i,j,t} c_{i,t-1})^{\frac{\eta-1}{\eta}} di\right]^{\frac{\eta}{\eta-1}} \tag{7}$$

$$\int_0^1 P_{i,t} c_{i,j,t} di + B_{j,t} = R_{t-1} B_{j,t-1} + W_t h_{j,t} + \Phi_t \quad \forall t \tag{8}$$

where $\Phi_t$ are firm profits treated as exogenous by households, $\sigma$ is the coefficient of relative risk aversion, $\kappa$ is the inverse Frisch elasticity of labor supply, $\eta$ is the elasticity of demand for differentiated goods, $c_{i,t} = \sum_{J=1}^{\infty} \int_{j \in J} c_{i,j,t} dj f(J)$ is aggregate consumption in sector i across all households, and where I have dropped the subscript $k$ to simplify terms.[24] Finally, $\tilde{\beta} = (1-g^d)\beta$ is the exit probability-adjusted discount factor. Further, $\theta_{i,j,t}$ is the deep habits parameter which is capturing the eventuality that household $j$ encounters and consumes a preferred variety in sector $i$ in period $t$. In particular, I assume that it is either zero when the household has not encountered her preferred variety yet or some constant when she has, i.e., $\theta_{i,j,t} = \mathbf{1}_{i,j,t}\theta$ where $\mathbb{E}[\mathbf{1}_{i,j,t}] = 1-(1-s)^J$ is the probability derived in the previous section and where $s$ is the parameter govern-

[24] Each household only consumes one variety per sector and the problem that firms producing different varieties in a given sector (or households consumption of a given variety in a sector) are symmetric.

ing the unconditional likelihood of having encountered a preferred variety.[25]

I abstract from potential heterogeneity due to differences in budget constraints and the accumulation of savings by assuming that savings decisions are relegated to a representative household who provides within and across cohort consumption insurance. Further, there is zero net supply of the risk-free asset such that in equilibrium $B_{j,t} = B_t = 0$ for all households and periods.[26] These assumptions yield a demand curve much like what is in the standard deep habits model with the only change being that the aggregate deep habits parameter, $\tilde{\theta} = (\theta s)/(1-(1-s)(1-g))$, is now a function of the age distribution. Specifically, aggregate deep habits increase as the population ages.

## 2.3. Firms

Production in this economy is comprised of two layers, consumption goods and intermediate goods (or inputs). The sole purpose of the second layer is to introduce another parameter which determines markups and is associated with the supply-side of the economy (the production elasticity of substitution between intermediate inputs). Changing this parameter will allow the model, in a reduced-form way, to capture alternative explanations of the rise in markups and flattening of the slope of the Phillips curve due to supply-side changes in areas such as production networks and the degree of market competition (Hoeynck, 2020; Fujiwara and Matsuyama, 2022; Rubbo, 2023). I describe each of the layers of production in the following sections.

### 2.3.1. Consumption goods production

Consumption goods are produced using a basket of intermediate inputs. Infinitely-lived firms produce varieties of differentiated consumption goods in monopolistic competitive markets and maximize the expected sum of profits dis-

[25] Note that the reference $\theta_{i,j,t} c_{i,t-1}$ for household j's consumption of $c_{i,j,t}$ is an aggregate consumption variable. This could be interpreted as adding a herding or *keeping up with the Joneses* aspect to the mechanism.

[26] One interpretation of this assumption is the presence of a well-functioning social security system.

counted by households' stochastic discount factor $q_t$ by choosing intermediate inputs demand and consumption goods prices. A firm producing good $i$ solves the following problem (variety $k$ is omitted for simplicity),

$$\begin{aligned} max \qquad & \mathbb{E}_t \sum_{s=0}^{\infty} q_{t+s}\Phi_{i,t+s} && (9) \\ \text{subject to:} \\ \Phi_{i,t} &= P_{i,t}c_{i,t} - \int_{m=0}^{1} P_{m,t}Y_{m,t}dm && (10) \\ c_{i,t} &= x_t\left[\frac{P_{i,t}}{P_t}\right]^{-\eta} - \tilde{\theta}c_{i,t-1} && (11) \\ c_{i,t} &\leq y_{i,t} = \left[\int_{m=0}^{1} Y_{m,t}^{\frac{\gamma-1}{\gamma}}\right]^{\frac{\gamma}{\gamma-1}} && (12) \end{aligned}$$

where $c_t \equiv \int c_{i,t}di$ is aggregate consumption, $Y_{m,t}$ are intermediate inputs with price $P_{m,t}$, and $\gamma$ is the production elasticity of substitution between intermediate inputs.

*2.3.2. Intermediate goods production*

The intermediate inputs to consumption goods are produced using labor by infinitely-lived monopolistic competitive firms who maximizes the expected sum of profits discounted by households' stochastic discount factors by choosing labor demand and intermediate input prices subject to Rotemberg price adjustment costs. A firm producing intermediate input $m$ solves the following problem,

$$\begin{aligned} max \qquad & \mathbb{E}_t \sum_{s=0}^{\infty} q_{t+s}\Phi_{m,t+s} && (13) \\ \text{subject to:} \\ \Phi_{m,t} &= P_{m,t}Y_{m,t} - W_t h_{m,t} - \frac{\delta}{2}P_{M,t}c_t\left(\frac{P_{m,t}}{P_{m,t-1}} - \pi^*\right)^2 && (14) \\ Y_{m,t} &= \int_{i=0}^{1} Y_{i,t}\lambda_{i,t}^{\gamma}\left[\frac{P_{m,t}}{P_t}\right]^{-\gamma} di && (15) \\ Y_{m,t} &\leq Ah_{m,t} && (16) \end{aligned}$$

where $\pi^*$ is an inflation target set by the monetary authority, $\delta$ is the cost of price adjustment parameter, $\lambda_{i,t}$ is the marginal costs of consumptions goods producers, and $P_{M,t} = \left[\int_{m=0}^{1} P_{m,t}^{1-\gamma}\right]^{\frac{1}{1-\gamma}}$ is the average price level for intermediate inputs. The productivity of labor inputs $A$ is the same across firms.

### *2.4. Monetary policy and aggregation*

I close the model with a description of monetary policy which follows a Taylor-type rule,

$$\frac{R_t}{R^*} = \left[\frac{R_{t-1}}{R^*}\right]^{\rho_r} \left[\frac{\pi_t}{\pi^*}\right]^{\alpha_\pi(1-\rho_r)} \left[\frac{y_t}{y^*}\right]^{\alpha_y(1-\rho_r)} exp(\varepsilon_{r,t}) \tag{17}$$

where $\pi_t = P_t/P_{t-1}$ is the gross inflation rate, $R^*$ and $y^*$ are the steady-state nominal rate and output respectively, and $\varepsilon_{r,t}$ are monetary policy surprises. The full set of aggregate equilibrium conditions implied by the model assumptions are reported in the Appendix. In the next section, I draw out the model's implications regarding factors driving steady state markups, the New Keynesian Phillips Curve, and the output-inflation trade-off faced by monetary policy.

## 3. Model implications

As a first step, I derive an expression for steady state markups in the model which is defined as the ratio of consumption good prices to productivity-adjusted nominal wages. The (deterministic) steady state markup $\mu$ is given by the steady state inverse marginal cost of intermediate inputs producers $\lambda_h$,

$$\begin{aligned} \mu &\equiv \lambda_h^{-1} = [\frac{\gamma-1}{\gamma}\lambda_i]^{-1} \\ \mu &= \left[\frac{\gamma}{(\gamma-1)}\right]\left[\frac{\eta}{(\eta-1)}\right]\left[\frac{1-\tilde{\theta}}{1-\tilde{\theta}\left(\frac{\eta-\tilde{\beta}}{\eta-1}\right)}\right] \end{aligned} \tag{18}$$

which is increasing in the degree of deep habits. Further, aging or less demographically dynamic economies (low $g$) feature higher average deep habits and thus higher markups. The model predicts that aging societies are characterized by larger average markups.

It should be noted that the extent to which deep habits affects markups also depend on the consumption elasticity of substitution $\eta$ and the discount factor $\tilde{\beta}$.[27] Specifically, the effect of deep habits on markups decrease as $\eta - \tilde{\beta}$ approaches $\eta - 1$ (e.g., as $\eta$ becomes larger or $\tilde{\beta}$ approaches 1).

Further, markups are decreasing in the production elasticity of substitution $\gamma$. If supply-side factors generate a decrease in the elasticity of substitution across intermediate inputs, then the level of markups in the model will increase.

## *3.1. The New Keynesian Phillips Curve*

To get an analytical expression for the New Keynesian Phillips Curve (NKPC) implied by the model, I take first order log approximations of the equilibrium equations to simplify the expressions. Define variables in *hats* as log-deviations from a zero inflation steady state, e.g., $\hat{y}_t \equiv log(y_t) - log(y^*)$. Further, by taking log approximations, assuming that products of log-deviations are approximately zero, and simplifying leads to the following three equations characterizing monetary policy, the New Keynesian IS curve, and the NKPC as well as two equations defining the evolution of marginal costs for consumption goods and intermediate inputs production.

$$\hat{r}_t = \rho_r \hat{r}_{t-1} + (1-\rho_r)[\alpha_\pi \hat{\pi}_t + \alpha_y \hat{y}_t] + \varepsilon_{r,t} \tag{19}$$

$$\hat{y}_t = \frac{1}{1+\tilde{\theta}} \mathbb{E}_t \hat{y}_{t+1} + \frac{\tilde{\theta}}{1+\tilde{\theta}} \hat{y}_{t-1} - \frac{1-\tilde{\theta}}{1+\tilde{\theta}} \frac{1}{\sigma} [\hat{r}_t - \mathbb{E}_t \hat{\pi}_{t+1}] \tag{20}$$

$$\hat{\pi}_t = \tilde{\beta} \mathbb{E}_t \hat{\pi}_{t+1} + \frac{\gamma - 1}{\delta} \left[ \hat{\lambda}_{h,t} - \hat{\lambda}_{i,t} \right] + \tilde{\beta} \mathbb{E}_t \hat{\lambda}_{i,t+1} - (1+\tilde{\beta}) \hat{\lambda}_{i,t} + \hat{\lambda}_{i,t-1} \tag{21}$$

$$\hat{\lambda}_{i,t} = \Theta_1 \hat{y}_t - \Theta_2 \mathbb{E}_t \hat{y}_{t+1} - \Theta_3 \hat{y}_{t-1} \tag{22}$$

$$\hat{\lambda}_{h,t} = (\kappa + \frac{\sigma}{1-\tilde{\theta}}) \hat{y}_t - \Theta_4 \hat{y}_{t-1} \tag{23}$$

[27]The discount factor enters the markup equation as it is the discount factor used by firms when maximizing profits. If firms and households have different discount factors, then the firm discount factor would be the relevant parameter for markups.

The reduced-form parameters $\Theta_1$ to $\Theta_4$ are functions of parameters $\{\tilde{\beta}, \tilde{\theta}, \eta, \sigma\}$ and are all equal to zero when $\tilde{\theta}$ is zero. In particular, these reduced-form parameters are strictly positive and increasing in deep habits whenever $\tilde{\theta} > 0$. This also means that without deep habits then $\hat{\lambda}_{i,t} = 0$ and the model simplifies to a standard New Keynesian model.

Before examining the NKPC, we first comment on the IS curve under deep habits. First, as one would expect, deep habits adds smoothing to output and the IS curve is no longer purely forward looking but is a function of a weighted average of past and expected future output. Second, deep habits attenuates the response of output (or demand) to interest rate and demand shocks. This already implies that larger interest rate movements are needed in order to stimulate or depress demand under deep habits. While significant in itself, a monetary authority would be more interested in the trade-off between output and inflation in response to interest rate changes. For this we have to refer to the NKPC.

As can be seen in equation 21 representing the marginal cost NKPC of the model, there are two marginal costs to take into account and one of them ($\hat{\lambda}_{i,t}$) is purely related to deep habits. This term adds leads and lags of output into the NKPC. We can substitute the equations for the marginal costs into the NKPC to derive the NKPC in terms of inflation and output:

$$\begin{aligned}
\hat{\pi}_t \;=\; & \tilde{\beta}\mathbb{E}_t\hat{\pi}_{t+1} + \left[\frac{\gamma-1}{\delta}\left(\kappa + \frac{\sigma}{1-\tilde{\theta}}\right) - \tilde{\beta}(\Theta_1+\Theta_3) - \left(1+\frac{\gamma-1}{\delta}\right)\Theta_1\right]\hat{y}_t \\
& -\Theta_2\tilde{\beta}^2\mathbb{E}_t\hat{y}_{t+2} + \left(\Theta_1 + \left(1+\tilde{\beta}+\frac{\gamma-1}{\delta}\right)\Theta_2\right)\tilde{\beta}\mathbb{E}_t\hat{y}_{t+1} - \Theta_2\tilde{\beta}\mathbb{E}_{t-1}\hat{y}_t \\
& +\left(\Theta_1 + \left(1+\tilde{\beta}+\frac{\gamma-1}{\delta}\right)\Theta_3 - \frac{\gamma-1}{\delta}\Theta_4\right)\hat{y}_{t-1} - \Theta_3\hat{y}_{t-2}
\end{aligned} \tag{24}$$

where the last two rows of equation 24 disappear and the coefficient on current output reduces to the standard slope of the NKPC without deep habits ($\tilde{\theta} = 0$). It should be noted that the slope of the marginal cost NKPC (equation 21) is unaffected by deep habits while the coefficient on contemporaneous output on the output-based NKPC (equation 24) falls as deep habits increases or the population ages. This would be consistent with recent results in Gagliardone et al. (2023) who find that the slope of the marginal cost NKPC remains steep while the relation between marginal cost and output has weakened over time.

With deep habits, the coefficient on current output tends to decrease as deep habits increase or, equivalently, as populations age. Further, leads and lags of output are now present in the NKPC such that the *slope* of the NKPC defined as the coefficient on current output is no longer a sufficient statistic describing the dynamic relationship between inflation and output in the NKPC.

In order to fully appreciate the implications of demographic aging and deep habits on the conduct of monetary policy, in the next section I conduct simulations of the model under alternative calibrations reflecting a young and vibrant economy and one with an aging population. Specifically, I use the calibrated model to draw out the responses of both inflation and output to monetary policy surprises and report how the output-inflation trade-off changes as the population ages.

### *3.2. Model-implied contribution of demographic aging to markups*

I illustrate the model-implied effects of aging on the output-inflation trade-off faced by monetary policy by calibrating the model to reflect two economies which significantly differ in the age distribution and firm market power. I pick conditions in Japan in the 1980s and 2010s as representative cases for these two scenarios.[28] This is because Japan is one of the textbook examples for an aging economy where the old-age dependency ratio increased from about 16% in the 1980s to about 30% in the 2010s. Moreover, average markups in Japan increased by about 24% over the same period.

For each period (1980-1985 and 2011-2016), annual data on life expectancy, population growth, as well as average markups from De Loecker and Eeckhout (2020) are averaged. I then calibrate the parameters $gb$ and $gd$ to best match average population growth and life expectancy, set the maximum value of deep habits $\theta$ so that the average deep habits across both periods is approximately 0.85, and set the parameter $s$ such that average deep habits flatten out at about

[28] One should keep in mind that the model is stylized and simple and any calibration of it should at best be interpreted as a back-of-the-envelope exercise rather than a full-fledged quantitative evaluation of the model fit to the data.

55 years of age.[29] Finally, I match average markups by varying the elasticity of substitution parameters $\eta$ and $\gamma$. Specifically, I set the two elasticity parameters approximately equal and match markups in the first period. I then calibrate a different $\gamma$ for the second period in order to match markups in the 2010s. Table 5 reports a comparison of the model and data in terms of the observables. The last three rows also report average deep habits implied by the parameters as well as the values of the elasticities of substitution required to match average markups.

Table 5: Model-implied vs. actual demographic features and markups

| | 1980-1985 | | 2011-2016 | |
|---|---|---|---|---|
| | Data | Model | Data | Model |
| Population growth | 0.688 | 0.688 | -0.141 | -0.141 |
| Life expectancy. | 76.901 | 76.897 | 83.398 | 83.400 |
| Markups | 1.036 | 1.036 | 1.280 | 1.280 |
| Average Deep habits | | 0.753 | | 0.947 |
| Consumption elasticity | | 56.913 | | 56.913 |
| Production elasticity | | 59.848 | | 4.969 |

*The table reports model-implied demographics and markups against the data for Japan and the periods 1980-1985 and 2011-2016. The last three rows also report the implied average deep habits given the demographics calibration and the value of the elasticity of substitution parameters required to match average markups.*

As there are a sufficient number of free parameters, the calibration is able to generate a decline in birth rates, an increase in life expectancy, and an increase in markups. The rest of the parameters are calibrated as standard in the literature. Table A.7 in the Appendix reports the calibrated values of the other parameters.

Given the model calibrations, we can also decompose the change in steady state markups from the 1980s to the 2010s into what is due to demographic changes and other factors captured by the change in the production elasticity of substitution $\gamma$. Table 6 reports the breakdown when I calibrate the model to the

[29] This is set to match the estimated marginal effects reported in Figure A.2 where the marginal contribution of 5-year age groups to average markups flattens at about 55-59 years of age. This also assumes that households enter the economy at age 15 such that 55 years of age is 160 periods in the model.

1980s, to the 2010s but without changing the demographic structure, and finally to the 2010s including the demographic changes. The first column reports the steady state markup while the second column reports the share of the change in markups relative to the 1980s.

Table 6: Decomposition of the change in markups

| | Level | Share |
|---|---|---|
| 1980-1985 Baseline | 1.036 | |
| 2011-2016 with no demog. change | 1.275 | 96.2 |
| 2011-2016 All changes | 1.280 | 100.0 |

*The table reports model-implied markups when the model is calibrated to match Japan for the periods 1980-1985 and 2011-2016. The first row reports the 1980-1985 baseline. The second row reports markups when the production elasticity of substitution $\gamma$ is allowed to increase to 2011-2016 levels but demographics parameters (and thus deep habits) are kept to 1980-1985 levels. Finally, the third row reports the 2011-2016 markups when both demographics and production elasticities are calibrated to 2011-2016.*

The calibration indicates that demographic changes only have a marginal impact on markups at 3.8% of the total change.[30] This is because the effect of deep habits on markups also depend on the consumption elasticity of substitution $\eta$ and the discount factor $\tilde{\beta}$ (see equation 18). In order for demographic changes to have a larger share of the increase in markups then either the consumption elasticity of substitution has to be lower at least in the second period (which would be consistent with what Curtis et al. (2024) find for US households) or the discount factor (of firms) would need to be lower than the calibrated value of 0.99. If, for instance, firms were to be more myopic, then changes in average deep habits would have stronger effects on average markups. The reason behind this feature is that firms know that when they raise prices today, their market share declines both today and in the future because of deep habits. Therefore a discount factor close to one for firms constrains their incentives to capitalize on inelastic demand today. Conversely, if firms have a shorter-term view of profits, then they would be more inclined to raise prices to take advantage of inelastic demand today.

[30] In contrast, population aging could potentially account for about 10% of the increase in markups for OECD countries based on the estimates from Table 2.

### 3.3. *Demographic aging and the effects of monetary policy surprises*

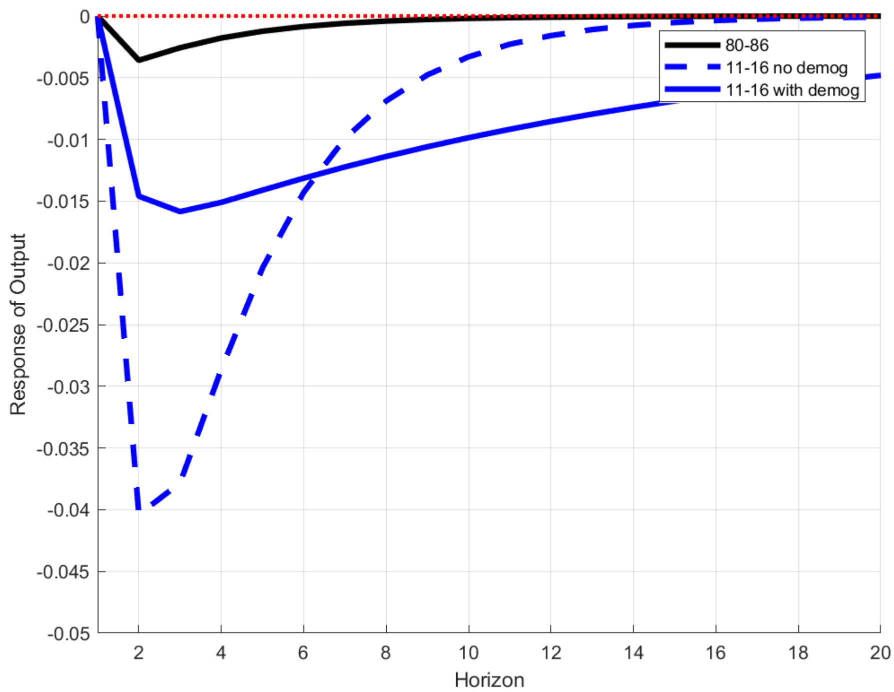
I now move on to the model's implications regarding demographic aging and the conduct of monetary policy. As noted in previous sections, the *slope* of the NKPC is no longer a sufficient statistic to characterize the trade-offs between inflation and output faced by monetary policy. Consequently, I use the model to generate responses of inflation and output to a monetary policy surprise and compare the response of output in the model when calibrated to the 1980s and the 2010s. The size of the shock is calibrated to generate a cumulative decline in the inflation rate of one percent over a fixed horizon of 5 years. Figure 1 plot the response of output under different calibrations of the model.[31]

The figure indicates a dramatically stronger response of output to a monetary policy surprise in the 2010s relative to the 1980s. That is, a monetary policy shock which lowers inflation by the same amount will significantly and more persistently reduce output in the 2010s relative to the 1980s. The assumption of Rotemberg price rigidities is key to this finding. Under this assumption, the model generates a link between (the increase in) steady state markups and the output cost of disinflation. Nevertheless, if one were to assume that the frequency of price adjustment is endogenous to the fickleness of consumer demand (i.e., if the frequency of price changes falls as consumers become more habitual in their consumption), then a similar result may be obtained in a state-dependent Calvo setting.

Demographic changes play an important role in increasing the output cost of disinflation. When the model is calibrated to keep demographic parameters to the level in the 1980s but for markups to increase only due to supply-side factors, we see that output falls by more in the short run but goes back to the steady state relatively quickly in about 4 years. However, with demographic changes, while the initial fall in output is attenuated, it is also more persistent and the cumulative fall in output over a 5 year horizon is about 10% larger than

[31] See Table A.8 in the Appendix for the cumulative response of output and inflation to a monetary policy surprise shock which generates a cumulative decline of inflation of one percent over 2, 5, and 20 years and across model calibrations.

Figure 1: Response of output and inflation to a monetary surprise: Japan




*The figure plots the model-implied responses of output to a monetary policy surprise shock when the model is calibrated to Japan in the 1980s and the 2010s. The size of the shock is calibrated to generate the same cumulative response of inflation across scenarios - one percent over 5 years. The solid black line reports the response of output for the 1980-1985 baseline. The dashed blue line reorts the response of output when the production elasticity of substitution is calibrated to 2011-2016 but demographic parameters remain at 1980-1985 levels. Finally, the solid blue line reports the impulse response when both demographics and elasticity parameters are calibrated to 2011-2016.*

in the calibration without demographic changes. This increases to about 40% if we consider a longer horizon of 20 years as output is still below the steady state after 5 years for the calibration with demographic changes.

The simulations indicate that demographic aging accounts for a disproportionately larger share of the increase in the output cost of disinflation relative to its share in the increase in markups. This is due to the increase in output persistence when average deep habits are higher. This is confirmed in simulation results from an alternative model where aging directly affects the consumers' elasticity of substitution and there are no deep habits. In this version of the model without deep habits, the contribution of aging to the increase in the output cost of disinflation is proportional to the contribution of aging to the increase in steady state markups.[32]

# 4. Testing the model implications

The simulated response of output to monetary surprises across different calibrations of the model reflecting demographic aging in the previous section presents a testable implication of the model. The model suggests that the output response to monetary tightening (which results in a standardized fall in inflation) should be increasing in the proportion of the elderly in the population. To test this implication, I run state-dependent local projections of the impact of monetary surprises on output and inflation where the relevant state is the old-age dependency ratio. To identify monetary surprises, I follow Jorda et al. (2020) and exploit the *trilemma* of international finance to obtain an instrument for monetary policy surprises in countries which peg their currencies.

I collect annual data from the macrofinance database of Jorda et al. (2017) for macroeconomic variables and the Trilemma instrument and the United Na-

[32] See Table A.9 in the Appendix. The alternative model, where the elasticities of substitution are assumed to decrease as households age, is similar to the one presented in Curtis et al. (2024) and is described in full in the Appendix. A key difference between the alternative model in the Appendix and that presented in Curtis et al. (2024) is that I assume that the elasticity of substitution monotonically decreases with age while Curtis et al. (2024) assumes that two types of households (young and old) have different elasticities of substitution.

tions Population Division for a long history of the old-age dependency ratio. The sample period is restricted to the years 1950 to 2016 and covers 16 developed countries which have pegged their currency at some point during the sample period.[33] The average old-age dependency ratio for countries in the sample went from 16.3 to 30.7 over this period. I then estimate the following equation via instrumental variables local projections,

$$y_{t+h,c} = \alpha_{c,h} + \Delta\hat{r}_{t,c}\beta_{1,h} + x_{t,c}\gamma_{1,h} + od_{t,c} \times \left[\Delta\hat{r}_{t,c}\beta_{2,h} + x_{t,c}\gamma_{2,h}\right] + \varepsilon_{t+h,c} \quad (25)$$

where $y_{t+h,c}$ is either real GDP or CPI inflation in country $c$ at year $t+h$, $\Delta\hat{r}_{t,c}$ is the change in the short-term interest rate instrumented with the *trilemma* approach of Jorda et al. (2020), $od_{t,c}$ is the old-age dependency ratio, and $x_{t,c}$ are a set of control variables. The set of control variables follows closely the specification in Jorda et al. (2020) and includes contemporaneous values of first differences in log real GDP per capita and CPI inflation (except when they are the dependent variable), log real consumption per capita, log real investment per capita, short and long term interest rates, log real house prices, log real stock returns, the credit to GDP ratio, and up to two lags of the same set of variables.[34] I estimate local projections for horizons of zero to four. Taking into account leads and lags, the resulting sample contains 538 observations.

To facilitate the estimation, the old-age dependency ratio has been standardized within the sample. All specifications include country fixed effects and standard errors are clustered by country as in Jorda et al. (2020). I recover the response of output to a monetary surprise $(\hat{\beta}_{1,h} + \hat{\beta}_{2,h} \times od)$ . To make an *apples-to-apples* comparison across different states, I normalize the size of the monetary policy shock to generate a one percent cumulative decline in inflation after four years.

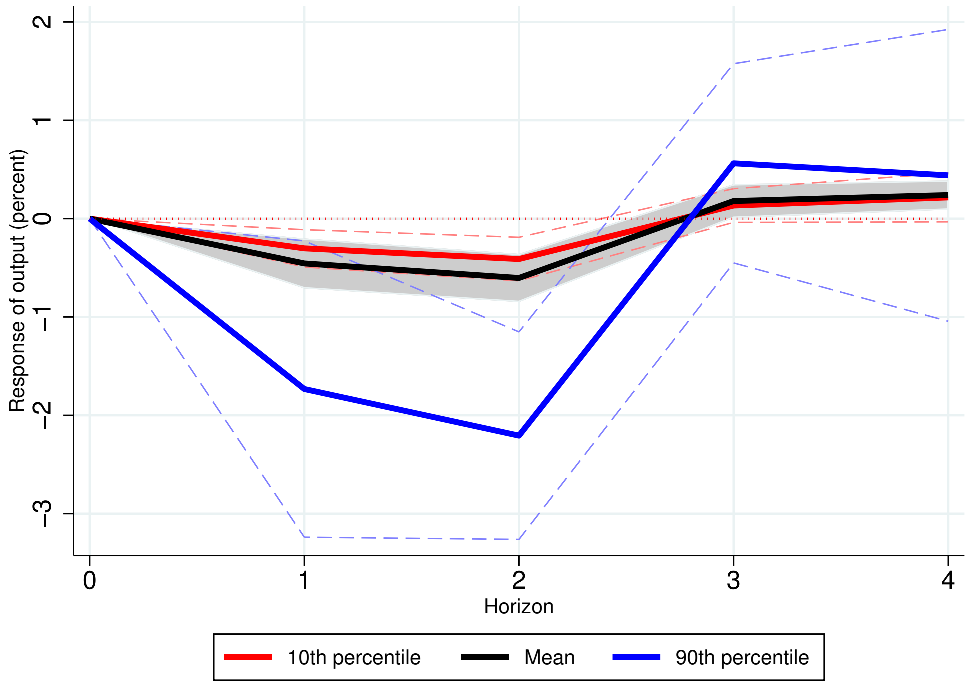
Figure 2 plots the impulse responses across three values of old-age dependency ratios. The black line reports the impulse response at the average old-age dependency ratio in the sample (21%), the red line is the corresponding impulse

[33]See Jorda et al. (2020) for further details on the construction of the Trilemma instrument. Summary statistics and the list of countries covered are reported in Table A.5 in the Appendix.

[34]Following Jorda et al. (2020), the control variables are also interacted with a dummy for the years 1973 to 1980 to address the *price puzzle*.

response for the 10th percentile (14% or -1.28 standard deviations) of the old-age dependency ratio, and the blue line is for when the old-age dependency ratio is equivalent to the 90th percentile (27%). The shaded area represent the 90% confidence interval around the impulse response at the average old-age dependency ratio while the dashed red and blue lines correspond to the 90% confidence intervals around the impulse responses for the 10th and 90th percentile of the old-age dependency ratio respectively.

Figure 2: Response of output to a monetary surprise: Trilemma IV




*The figure plots the estimated response of real GDP to a monetary policy surprise using the Trilemma instrumental variable identification when the old-age dependency ratio is equivalent to the 10th (14%, red), mean (21%, black), and 90th percentile (27%, blue) respectively. For each impulse response, the size of the shock has been calibrated to generate a cumulative fall of inflation of one percent by horizon four. The gray shaded area and dashed red and blue lines represent the corresponding 90% confidence intervals.*

As predicted by the model, Figure 2 shows that the output cost of a monetary tightening is much larger when the old-age dependency ratio is higher. This is driven by the weaker impact of monetary tightening on inflation when the old-age dependency ratio is higher. Since monetary policy surprises are less effective in lowering inflation when the old-age dependency ratio is higher, a larger monetary policy intervention would be necessary to bring down inflation by one percent over a four year horizon. Table 7 summarizes this finding. The first four rows of the table report the cumulative output loss from horizons one to four. The last row reports the size of the monetary policy surprise that is needed to generate a cumulative fall in inflation of one percent in four years and is the shock size which generates the output loss in the previous rows. Each column reports results for a different level of the old-age dependency ratio.

Table 7: Cumulated response of output to monetary policy surprises: Trilemma IV

| Old-age dep. ratio: | 10th percentile | Sample Mean | 90th percentile |
|---|---|---|---|
| $h = 1$ | -0.302 | -0.456 | -1.733 |
| $h = 2$ | -0.713 | -1.059 | -3.939 |
| $h = 3$ | -0.580 | -0.880 | -3.377 |
| $h = 4$ | -0.365 | -0.640 | -2.937 |
| Shock size | 0.370 | 0.660 | 3.080 |

*The table reports the cumulated response of output to a monetary tightening using the Trilemma instrumental variable identification. Each column reports results for different states of the old-age dependency ratio. The 10th percentile corresponds to a ratio of 14%, the sample mean is 21%, and the 90th percentile is 27%. The first four rows report the cumulated response of log real GDP per capita at horizons zero to four. The last row reports the size of the monetary policy surprise which generates the impulse responses and is consistent with a cumulated fall in inflation of one percent by four years.*

As indicated in the last row of Table 7, the size of the monetary policy surprise needed to bring down inflation by one percent in four years is about 8 times larger when the old-age dependency ratio is at the 90th percentile (or equivalent to 27%) relative to when it is at the 10th percentile (14%). The cumulative output loss after four years (penultimate row) is also eight times larger. Altogether, these results are consistent with the notion that the slope of the NKPC flattens as the population ages.

It should be noted that the results from this exercise pertain to an exogenous innovation to the policy rate. The actual responses of output relative to inflation in the case when monetary policy endogenously responds to an exogenous (inflationary) shock may differ and depend also on the source or type of shock that monetary policy is responding to. The analysis here also does not account for how population aging could potentially alter the transmission of these exogenous shocks to output and inflation and thus the corresponding scale of monetary policy intervention that would be needed to meet a set goal. Nevertheless, the empirical exercise is designed to best approximate the simulated responses from the model and thus the testable model-implied prediction.

# 5. Conclusion

This paper explores the connection between demographic aging, firm markups, and the slope of the New Keynesian Phillips Curve. Motivated by the evidence in the literature and my own findings with respect to the link between aging, markups, and the preference for non-price characteristics as households age, I focus on a specific channel - that households accumulate habits as they age - and develop a New Keynesian Deep Habits model around this hypothesis. I then use the model to show that demographic aging also leads to a flattening of the New Keynesian Phillips Curve. More broadly, I show that demographic aging can significantly worsen the output-inflation trade-off faced by monetary policy. These results suggest that the challenges faced by monetary policy may become more pronounced as populations age.

The model presented here is intentionally parsimonious and does not capture other channels proposed in the literature linking aging with the slope of the New Keynesian Phillips Curve through labor markets, business dynamism, and the general organization of production in the economy. Exploring interactions between aging-induced changes in aggregate deep habits and these complementary channels is left for future work. Another important and complementary direction for future research is on how aging affects the transmission of other shocks to inflation and output and consequently how aging also affects the scale of monetary policy interventions needed to meet a central bank's goals.

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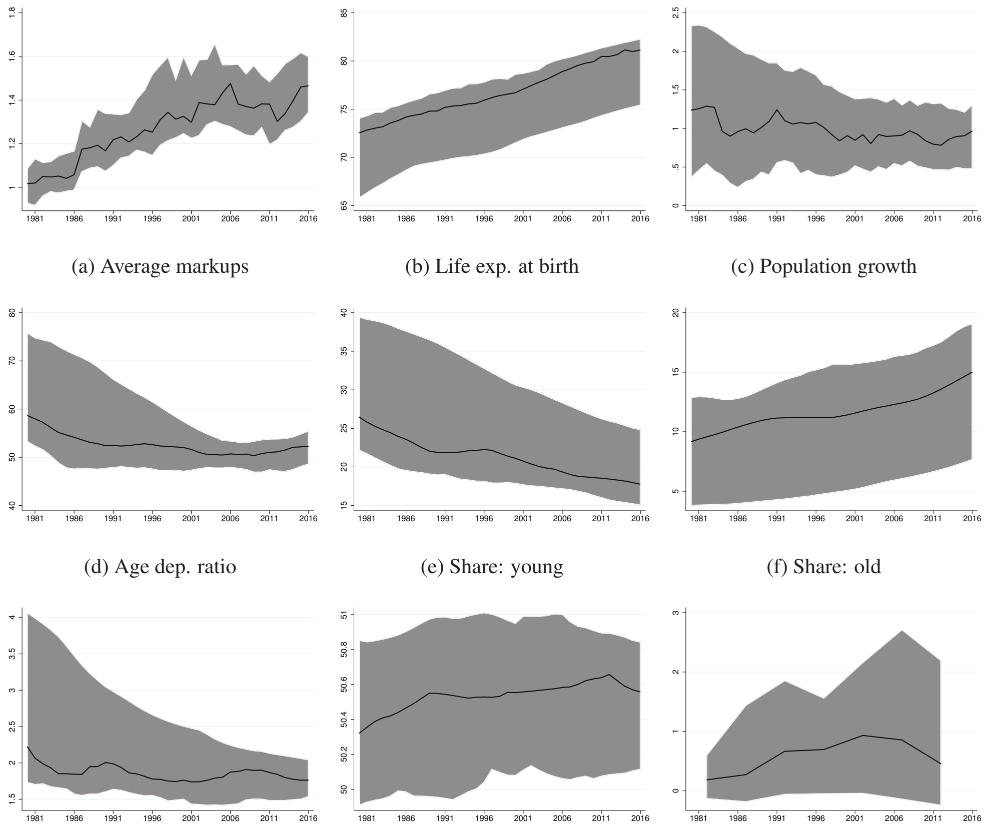
# Appendix

## *Appendix A.1. Appendix Figures*

Figure A.1: Demographics and markups over time



(a) Average markups

(b) Life exp. at birth

(c) Population growth

(d) Age dep. ratio

(e) Share: young

(f) Share: old

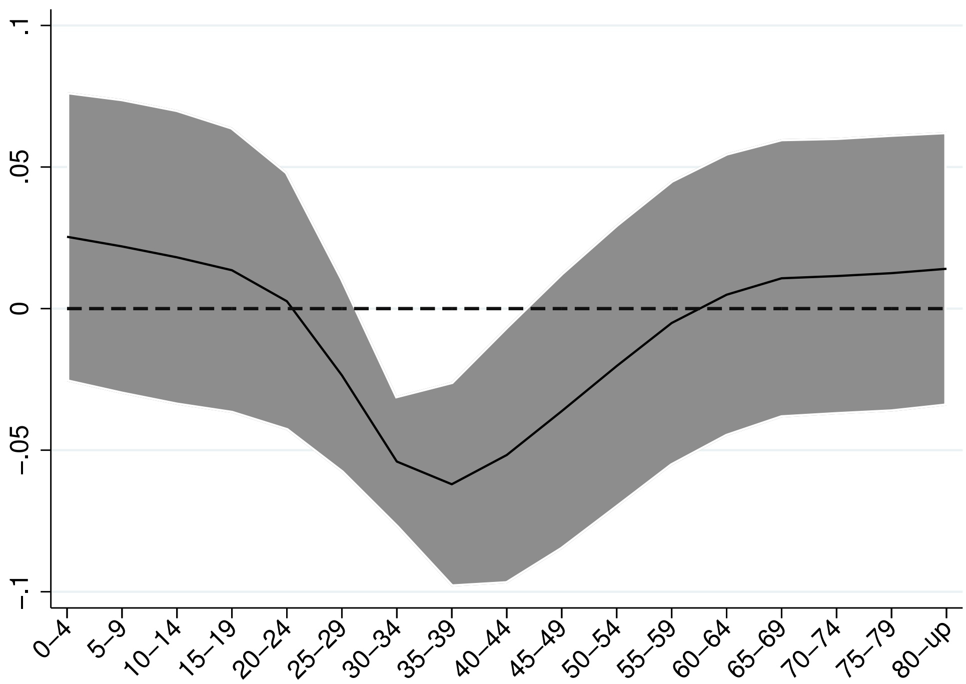
(g) Fertility rate

(h) Share: Female

(i) Net migration

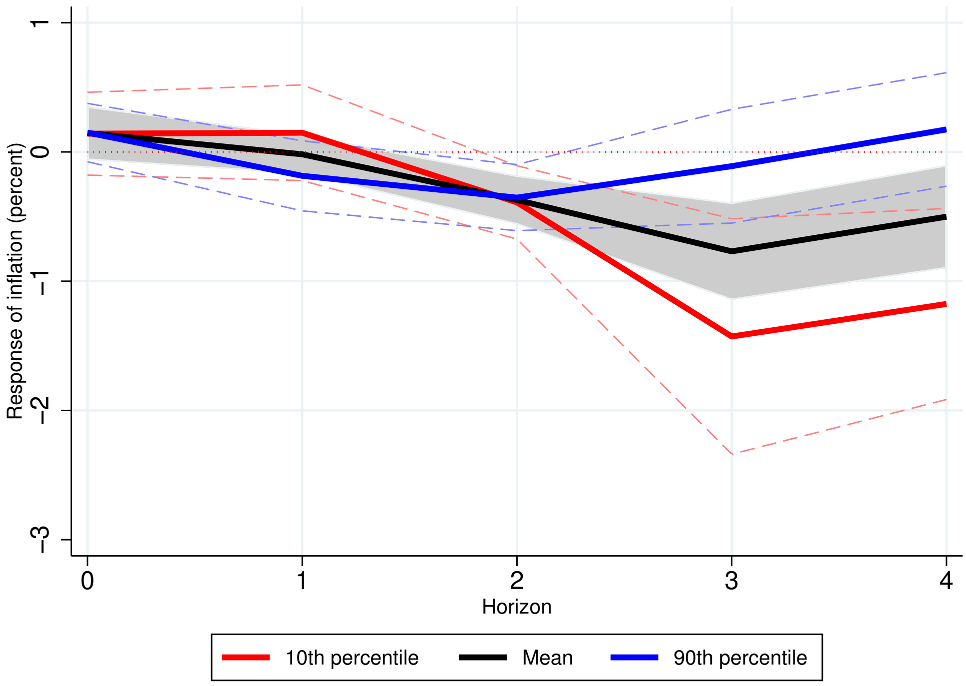
*The figures plot the evolution of several demographics variables and average markups of 40 countries over time. The shaded area represents the interquartile range while the black lines reports the median values.*

Figure A.2: Marginal effects of age group shares on markups




*The figures plot the implied marginal effects of each age sub-group from a factor transform corresponding to coefficient estimates from regression specification (1) in Table A.4 and using the factor loadings of the 17 age categories. The shaded area represents the 68% interval while the solid black line indicates the point estimates.*

Figure A.3: State dependent local projection response of inflation to a monetary surprise: Trilemma IV




*The figure plots the estimated response of CPI inflation to a monetary policy surprise using the Trilemma instrumental variable identification when the old-age dependency ratio is equivalent to 14 (red), 21 (black), and 27% (blue) which are the 10th, mean, and 90th percentiles in the sample. The size of the shock is a 1 percentage point increase in the short term interest rate. The gray shaded area and dashed red and blue lines represent the corresponding 90% confidence intervals.*

## *Appendix A.2. Appendix Tables*

Table A.1: Country panel data descriptive statistics

| | Mean | St. dev. | Obs. | Description |
|---|---|---|---|---|
| Markups | 1.34 | 0.31 | 1382 | Average markups |
| Age dependency ratio (total) | 54.57 | 10.81 | 1480 | Share of young (0-14) and old (65+) to working age pop. |
| Share young to total pop. | 24.37 | 8.22 | 1480 | Share of young (0-14) to total pop. |
| Share old to total pop. | 10.64 | 5.27 | 1480 | Share of old (65+) to total pop. |
| Life exp. at birth (years) | 74.22 | 6.24 | 1480 | Life expectancy at birth, total (years) |
| Population growth(annual %) | 1.08 | 0.82 | 1479 | Population growth in annual % |
| Fertility rate | 2.18 | 0.94 | 1480 | Fertility rate (births per woman) |
| Share female to total pop. | 50.42 | 0.90 | 1480 | Share of felae to total pop. |
| Net migration (% of pop.) | 0.97 | 1.88 | 280 | Net migration to total pop. |
| Real GDP growth (annual %) | 3.30 | 3.59 | 1478 | Real GDP growth in annual % |
| Real GDP per capita | 24609.52 | 19630.46 | 1478 | GDP per capita in constant 2010 USD |
| CPI inflation | 24.30 | 250.70 | 1404 | Consumer price index (2010=100) inflation in annual % |
| Unemployment rate | 6.96 | 4.77 | 1122 | Unemployment rate as % of labor force |
| Currrent Account to GDP | 0.24 | 5.40 | 1339 | Current account balance as % of GDP |
| Trade (% of GDP) | 74.70 | 67.61 | 1478 | Total trade as % of GDP |
| External balance (% of GDP) | 1.56 | 6.14 | 1478 | External balance on Goods and Sercices as % of GDP |
| Gov. Cons. Exp. (% of GDP) | 15.96 | 5.03 | 1471 | General government final consumption exp. as % of GDP |
| Gross savings (% of GDP) | 24.79 | 8.03 | 1337 | Gross savings as % of GDP |
| Labor force part. rate | 60.65 | 7.50 | 1308 | Labor force participation rate as % to population aged15+ |
| Services value-added (% of GDP) | 57.13 | 9.70 | 1225 | Services sector value added as % of GDP |
| Manufacturing value-added (% of GDP) | 17.57 | 5.68 | 1244 | Manufacturing value added as % of GDP |
| Market cap of listed firms (% of GDP) | 77.87 | 113.39 | 1147 | Market cap. of listed dom. firms as % of GDP |
| Private domestic credit (% of GDP) | 80.31 | 51.05 | 1221 | Domestic credit to private sector as % of GDP |
| Population density | 414.85 | 1295.86 | 1460 | People per square kilometer of land area |
| Share rural to total pop. | 29.44 | 18.69 | 1480 | Rural population to total pop. |

*Data is annual covering 40 countries from 1980-2016. Average annual markups are obtained from De Loecker and Eeckhout (2020). The rest of the variables are sourced from the World Bank World Development Indicators database.*

Table A.2: Country panel data samples by country

| | Markups | | Age dep. ratio | | | Markups | | Age dep. ratio | |
|---|---|---|---|---|---|---|---|---|---|
| Country | First | Last | First | Last | Country | First | Last | First | Last |
| ARG | 1986 | 2016 | 1980 | 2016 | IRL | 1980 | 2016 | 1980 | 2016 |
| AUS | 1980 | 2016 | 1980 | 2016 | ITA | 1980 | 2016 | 1980 | 2016 |
| AUT | 1980 | 2016 | 1980 | 2016 | JPN | 1980 | 2016 | 1980 | 2016 |
| BEL | 1980 | 2016 | 1980 | 2016 | KOR | 1980 | 2016 | 1980 | 2016 |
| BRA | 1980 | 2009 | 1980 | 2016 | MEX | 1980 | 2016 | 1980 | 2016 |
| CAN | 1980 | 2016 | 1980 | 2016 | MYS | 1980 | 2016 | 1980 | 2016 |
| CHE | 1980 | 2016 | 1980 | 2016 | NLD | 1980 | 2016 | 1980 | 2016 |
| CHL | 1985 | 2016 | 1980 | 2016 | NOR | 1980 | 2016 | 1980 | 2016 |
| CHN | 1982 | 2016 | 1980 | 2016 | NZL | 1980 | 2016 | 1980 | 2016 |
| COL | 1987 | 2016 | 1980 | 2016 | PAK | 1988 | 2016 | 1980 | 2016 |
| DEU | 1980 | 2016 | 1980 | 2016 | PER | 1987 | 2016 | 1980 | 2016 |
| DNK | 1980 | 2016 | 1980 | 2016 | PHL | 1988 | 2016 | 1980 | 2016 |
| ESP | 1980 | 2016 | 1980 | 2016 | PRT | 1985 | 2016 | 1980 | 2016 |
| FIN | 1980 | 2016 | 1980 | 2016 | SGP | 1980 | 2016 | 1980 | 2016 |
| FRA | 1980 | 2016 | 1980 | 2016 | SWE | 1980 | 2016 | 1980 | 2016 |
| GBR | 1980 | 2016 | 1980 | 2016 | THA | 1987 | 2016 | 1980 | 2016 |
| GRC | 1980 | 2016 | 1980 | 2016 | TUR | 1987 | 2016 | 1980 | 2016 |
| HKG | 1982 | 2016 | 1980 | 2016 | USA | 1980 | 2016 | 1980 | 2016 |
| IDN | 1989 | 2016 | 1980 | 2016 | VEN | 1987 | 2016 | 1980 | 2016 |
| IND | 1989 | 2016 | 1980 | 2016 | ZAF | 1982 | 2016 | 1980 | 2016 |

*The table reports the year of the first and last observations for average markups and age dependency ratios for each country in the sample. Country codes are ISO-3166 alpha-3 three letter country codes.*

Table A.3: Univariate regressions of markups on demographic factors

| Dep. var.: Markups | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Age dependency ratio (total) | 0.002 | | | | | |
| | (0.00) | | | | | |
| Life exp. at birth (years) | | 0.006 | | | | |
| | | (0.00) | | | | |
| Population growth(annual %) | | | 0.033 | | | |
| | | | (0.01) | | | |
| Fertility rate | | | | 0.022 | | |
| | | | | (0.01) | | |
| Share female to total pop. | | | | | 0.016 | |
| | | | | | (0.01) | |
| Net migration (% of pop.) | | | | | | -0.011 |
| | | | | | | (0.01) |
| Constant | 1.239 | 0.886 | 1.310 | 1.298 | 0.538 | 1.340 |
| | (0.04) | (0.10) | (0.01) | (0.02) | (0.41) | (0.02) |
| Observations | 1382 | 1382 | 1381 | 1382 | 1382 | 263 |
| Adj. R-sq. | 0.003 | 0.012 | 0.006 | 0.003 | 0.001 | 0.001 |

*Robust standard errors reported in parentheses. The table reports univariate regressions of average markups on several demographic characteristics. Data is annual and covers the period 1980-2016 for 40 countries.*

Table A.4: Factor and polynomial shrinkage regression results

| Dep. var.: Markups | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Age dist. factor 1 | -0.011 | 0.009 | | |
| | (0.05) | (0.05) | | |
| Age dist. factor 2 | -0.070 | -0.054 | | |
| | (0.03) | (0.02) | | |
| Age dist. factor 3 | 0.037 | 0.033 | | |
| | (0.01) | (0.01) | | |
| Age dist. factor 4 | -0.019 | -0.009 | | |
| | (0.01) | (0.01) | | |
| Age dist. poly 1 | | | 0.039 | 0.055 |
| | | | (0.02) | (0.02) |
| Age dist. poly 2 | | | -0.011 | -0.013 |
| | | | (0.01) | (0.00) |
| Age dist. poly 3 | | | 0.001 | 0.001 |
| | | | (0.00) | (0.00) |
| Age dist. poly 4 | | | -0.000 | -0.000 |
| | | | (0.00) | (0.00) |
| Share female to total pop. | -0.090 | -0.071 | -0.062 | -0.061 |
| | (0.04) | (0.03) | (0.04) | (0.04) |
| D.Life exp. at birth (years) | 0.029 | 0.035 | 0.029 | 0.041 |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| Population growth(annual %) | -0.012 | -0.012 | -0.007 | -0.008 |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| L.Markups | 0.387 | 0.469 | 0.388 | 0.462 |
| | (0.20) | (0.11) | (0.20) | (0.11) |
| Additional controls | YES | YES | YES | YES |
| Fixed effects | Y,C | Y | Y,C | Y |
| Observations | 628 | 628 | 628 | 628 |
| Adj. R-sq. | 0.810 | | 0.810 | |
| AR(1) p-value | | 0.000 | | 0.000 |
| AR(2) p-value | | 0.741 | | 0.679 |

*Cluster-robust standard errors (by country) for the panel fixed effects regression (odd columns) and robust standard errors for the dynamic panel regressions (even columns) are reported in parentheses. The table reports multivariate regressions of average markups on factor and polynomial shrinkage of the age distribution along with other demographic factors and several control variables. Data is annual and covers the period 1980-2016 for 40 countries. For the Arellano-Bover-Blundell-Bond dynamic panel regressions, p-values from tests of residual serial correlation up to 2 lags are also reported. Control variables used, but not reported, are real GDP, the ratio of current account to GDP, the ratio of total trade to GDP, the ratio of government expenditures to GDP, the savings to GDP rate, the share of Services sector value-added to GDP, the labor force participation rate, the unemployment rate, population density, the ratio of stock market capitalization to GDP, the ratio of domestic credit to GDP, and a linear time trend. Panel fixed effects regressions include year and country fixed effects.*

Table A.5: State-dependent local projections data summary statistics

| | Mean | St. dev. | Obs. |
|---|---|---|---|
| Old-age dependency ratio | 20.74 | 5.15 | 544 |
| Log CPI | 411.97 | 89.60 | 544 |
| Log real GDP per capita | 418.79 | 38.34 | 544 |
| Short term interest rate | 6.08 | 4.27 | 544 |
| Long term interest rate | 7.23 | 3.67 | 544 |
| Log real consumption per capita | 418.71 | 37.51 | 544 |
| Log real investment per capita | -426.30 | 432.79 | 544 |
| Credit to GDP ratio | 0.75 | 0.35 | 544 |
| Log real house price | -13.50 | 48.07 | 544 |
| Log real stock price | -7.09 | 328.42 | 544 |

*Data is annual covering 16 countries from 1950-2016. Macroeconomic variables are obtained from Jorda et al. (2017) while the old-age dependency ratios are obtained from the United Nations Population Division.*

Table A.6: State-dependent local projections data country coverage

| Country | Obs. | Country | Obs. |
|---|---|---|---|
| Australia | 29 | Italy | 37 |
| Belgium | 63 | Japan | 18 |
| Canada | 39 | Netherlands | 25 |
| Denmark | 64 | Portugal | 26 |
| Finland | 59 | Spain | 43 |
| France | 57 | Sweden | 26 |
| Germany | 7 | Switzerland | 25 |
| Ireland | 2 | UK | 24 |

*The table reports the number of observations per country used in the state-dependent local projections analysis.*

### *Appendix A.3. Model Appendix*

The households' problem yield the following optimality conditions,

$$c_{i,j,t} = x_{j,t}\left[\frac{P_{i,t}}{P_t}\right]^{-\eta} + \theta_{i,j,t}c_{i,t-1} \tag{A.1}$$

$$h^{\kappa}_{j,t} = x^{-\sigma}_{j,t}W_t/P_t \tag{A.2}$$

where

$$P_t = \left[\int_0^1 P^{1-\eta}_{i,t}di\right]^{\frac{1}{1-\eta}} \tag{A.3}$$

Here, the aggregate price level is given by equation A.3 and aggregate consumption for sector $i$ (which is the same across all the varieties in that sector) is the sum of consumption across all households by age group ($c_{i,t} = \sum_{J=1}^{\infty} c_{i,J,t}f(J)$). In turn, consumption of all households of age J is just the sum of individual consumption, $c_{i,J,t} = \int_{j\in J} c_{i,j,t}$.

A symmetric equilibrium for households within the same age group yield the Euler equation,

$$x^{-\sigma}_{J,t} = \tilde{\beta}_t R_t \mathbb{E}_t[x^{-\sigma}_{J,t+1}P_t/P_{t+1}] \tag{A.4}$$

and aggregating across households in a symmetric equilibrium yields the aggregate Euler and demand equations,

$$x^{-\sigma}_t = \tilde{\beta}_t R_t \mathbb{E}_t[x^{-\sigma}_{t+1}P_t/P_{t+1}] \tag{A.5}$$

$$c_{i,t} = x_t\left[\frac{P_{i,t}}{P_t}\right]^{-\eta} + \tilde{\theta}c_{i,t-1} \tag{A.6}$$

where $x_t \equiv \sum_{J=1}^{\infty} x_{J,t}f(J)$ while $c_{i,t} \equiv \sum_{J=1}^{\infty} c_{i,J,t}f(J)$ and,

$$\tilde{\theta} \equiv \sum_{J=1}^{\infty} \theta_{i,J,t}f(J) = \theta s[1-(1-s)(1-g)]^{-1} \tag{A.7}$$

Note here that the age distribution is crucial to average deep habits $\tilde{\theta}$. A young and dynamic population with high entry and exit of households (large $g$) exhibits lower habit persistence than an aging population with low entry and exit (small $g$). For instance, at the extreme where agents live for one period

($g = 1$), aggregate deep habits is proportional to the relative size of preferred sets, $\tilde{\theta} = \theta s$. On the other hand, when agents are infinitely-lived with no entry and exit ($g = 0$) then deep habits are maximized and $\tilde{\theta} = \theta$. The parameter $s$ governs the speed at which households develop deep habits. When $s$ is zero then there are no deep habits ($\tilde{\theta} = 0$) and when all varieties are preferred ($s = 1$) then deep habits are maximized ($\tilde{\theta} = \theta$).

The solution to the consumption goods firms' problem yield the following optimality conditions,

$$\begin{aligned} P_{m,t}/P_t &= \lambda_{i,t}[Y_{i,t}/Y_{m,t}]^{1/\gamma} && \text{(A.8)} \\ P_t\lambda_{d,t} + P_t\lambda_{i,t} &= P_{i,t} + \tilde{\theta}\mathbb{E}_t\frac{q_{t+1}}{q_t}P_{t+1}\lambda_{d,t+1} && \text{(A.9)} \\ P_{i,t}c_{i,t} &= \eta\lambda_{d,t}P_t(c_{i,t} - \tilde{\theta}c_{i,t-1}) && \text{(A.10)} \end{aligned}$$

where $\lambda_{i,t}$ is the multiplier on production (marginal cost, equation 12) and $\lambda_{d,t}$ is the multiplier on demand (equation 11). Equation A.8 can be rearranged to the demand for input $Y_{m,t}$ by aggregating across sectors.

$$Y_{m,t} = \int_{i=0}^{1} Y_{i,t}\lambda_{i,t}^{\gamma}\left[\frac{P_{m,t}}{P_t}\right]^{-\gamma} di \qquad \text{(A.11)}$$

The solution to the intermediate inputs firms' problem yield the following optimality conditions,

$$\begin{aligned} W_t/P_t &= \lambda_{h,t}A_t && \text{(A.12)} \\ P_{m,t} &= P_t\lambda_{m,t} + P_t\lambda_{h,t} && \text{(A.13)} \\ Y_{m,t} &= \gamma\lambda_{m,t}\int\lambda_{i,t}^{\gamma}Y_{i,t}di\left[\frac{P_{m,t}}{P_t}\right]^{-\gamma-1} + \delta c_t\frac{P_{M,t}}{P_{m,t-1}}\left(\frac{P_{m,t}}{P_{m,t-1}} - \pi^*\right) \\ &\quad -\delta\mathbb{E}_t\frac{q_{t+1}}{q_t}c_{t+1}\frac{P_{M,t+1}}{P_{m,t}}\frac{P_{m,t+1}}{P_{m,t}}\left(\frac{P_{m,t+1}}{P_{m,t}} - \pi^*\right) && \text{(A.14)} \end{aligned}$$

where $\lambda_{h,t}$ is the multiplier on production (marginal cost, equation 16) and $\lambda_{m,t}$ is the multiplier on demand (equation 15).

Aggregation, a symmetric equilibrium and market-clearing conditions yield the following equations which characterize the model.

$$
\begin{aligned}
x_t &= c_t - \tilde{\theta} c_{t-1} && \text{(A.15)}\\
h_t^{\kappa} &= x_t^{-\sigma} w_t && \text{(A.16)}\\
x_t^{-\sigma} &= \tilde{\beta} R_t \mathbb{E}_t x_{t+1}^{-\sigma} \pi_{t+1}^{-1} && \text{(A.17)}\\
\tilde{\beta} &= (1-g^d)\beta && \text{(A.18)}\\
\lambda_{i,t} + \lambda_{d,t} &= 1 + \tilde{\theta}\tilde{\beta}\mathbb{E}_t \left[\frac{x_{t+1}}{x_t}\right]^{-\sigma} \lambda_{d,t+1} && \text{(A.19)}\\
\lambda_{d,t} &= c_t/(\eta x_t) && \text{(A.20)}\\
\lambda_{i,t}/\lambda_{i,t-1} &= \pi_{m,t}/\pi_t && \text{(A.21)}\\
w_t &= A_t \lambda_{h,t} && \text{(A.22)}\\
\lambda_{m,t} + \lambda_{h,t} &= \lambda_{i,t} && \text{(A.23)}\\
y_t(1-\gamma\frac{\lambda_{m,t}}{\lambda_{i,t}}) &= \delta c_t \pi_{m,t}(\pi_{m,t} - \pi^*) \\
&\quad -\delta\tilde{\beta}\mathbb{E}_t \left[\frac{x_{t+1}}{x_t}\right]^{-\sigma} c_{t+1}\frac{\lambda_{i,t+1}}{\lambda_{i,t}}\pi_{m,t+1}(\pi_{m,t+1} - \pi^*) && \text{(A.24)}\\
c_t &= y_t - \frac{\delta}{2} c_t (\pi_{m,t} - \pi^*)^2 && \text{(A.25)}\\
y_t &= A h_t && \text{(A.26)}
\end{aligned}
$$

where $\pi_{m,t} = P_{m,t}/P_{m,t-1}$, $w_t = W_t/P_t$, $h_t = \int h_{i,t} di = \sum h_{j,t} f(j)$, and $y_t = \int y_{i,t} di$. Equations 17 and A.15 to A.26 complete the description of equilibrium.

The system of equations above can be reduced to a few equations after log-linearizing around the deterministic steady state:

$$
\begin{aligned}
\hat{y}_t &= \frac{1}{1+\tilde{\theta}}\mathbb{E}_t \hat{y}_{t+1} + \frac{\tilde{\theta}}{1+\tilde{\theta}}\hat{y}_{t-1} - \frac{1-\tilde{\theta}}{1+\tilde{\theta}}\frac{1}{\sigma}[\hat{r}_t - \mathbb{E}_t \hat{\pi}_{t+1}] && \text{(A.27)}\\
\hat{\pi}_t &= \tilde{\beta}\mathbb{E}_t \hat{\pi}_{t+1} + \frac{\gamma-1}{\delta}\left[\hat{\lambda}_{h,t} - \hat{\lambda}_{i,t}\right] + \tilde{\beta}\mathbb{E}_t \hat{\lambda}_{i,t+1} - (1+\tilde{\beta})\hat{\lambda}_{i,t} + \hat{\lambda}_{i,t-1} && \text{(A.28)}\\
\hat{\lambda}_{i,t} &= \Theta_1 \hat{y}_t - \Theta_2 \mathbb{E}_t \hat{y}_{t+1} - \Theta_3 \hat{y}_{t-1} && \text{(A.29)}\\
\hat{\lambda}_{h,t} &= (\kappa + \frac{\sigma}{1-\tilde{\theta}})\hat{y}_t - \Theta_4 \hat{y}_{t-1} && \text{(A.30)}
\end{aligned}
$$

These equations, along with a description of monetary policy, summarizes the model. The reduced-form parameters $\Theta_i$ are given by the following:

$$\Theta_1 = \left[\frac{\tilde{\theta}}{1-\tilde{\theta}}\right]\left[\frac{1+\tilde{\beta}\sigma+\tilde{\theta}\tilde{\beta}(1+\sigma)}{\eta-1-\tilde{\theta}(\eta-\tilde{\beta})}\right] \tag{A.31}$$

$$\Theta_2 = \left[\frac{\tilde{\theta}}{1-\tilde{\theta}}\right]\left[\frac{\tilde{\theta}+\sigma}{\eta-1-\tilde{\theta}(\eta-\tilde{\beta})}\right] \tag{A.32}$$

$$\Theta_3 = \left[\frac{\tilde{\theta}}{1-\tilde{\theta}}\right]\left[\frac{1+\tilde{\theta}\tilde{\beta}\sigma}{\eta-1-\tilde{\theta}(\eta-\tilde{\beta})}\right] \tag{A.33}$$

$$\Theta_4 = \left[\frac{\tilde{\theta}}{1-\tilde{\theta}}\right]\sigma \tag{A.34}$$

Note that all of these reduced-form parameters are increasing in the deep habits parameter and therefore demographic aging.

Table A.7: Model calibrated parameters

| Parameter | | Symbol | Value | Target |
|---|---|---|---|---|
| | Discount factor | $\beta$ | 0.99 | Annual real rate of 4% |
| | Risk aversion | $\sigma$ | 3.0 | Following Ravn et al. (2010) |
| | Inverse labor elasticity | $\kappa$ | 1.0 | Following Fernandez-Villaverde et al. (2015) |
| | Demand elasticity | $\eta$ | 56.91 | Match average markups in Japan over 1980-1985 |
| | Production elasticity | $\gamma$ | 59.85,4.97 | Match average markups in Japan over 1980-1985 and 2011-2016 |
| | Price rigidity | $\delta$ | 187 | Average Phillips curve slope equivalent to Calvo parameter of 0.75 |
| | Maximum habits | $\theta$ | 1.02 | Average deep habits of 0.85 as in Ravn et al. (2010) |
| | Deep habits rate | $s$ | 0.03 | Deep habits flatten out at age 55 years |
| | Birth rate | $gb$ | 0.011,0.002 | Population growth in Japan over 1980-1985 and 2011-2016 |
| | Death rate | $gd$ | 0.004-0.0037 | Life expectancy in Japan over 1980-1985 and 2011-2016 |
| Monetary policy rule | | | | |
| | Persistence | $\rho_r$ | 0.70 | Following Fernandez-Villaverde et al. (2015) |
| | Inflation coefficient | $\alpha_\pi$ | 1.5 | Conventional values |
| | Output coefficient | $\alpha_y$ | 0.0 | Conventional values |

Table A.8: Response of output to monetary policy surprises

| Horizon | 2 year | 5 year | 20 year |
|---|---|---|---|
| 1980-1985 Baseline | -0.011 | -0.012 | -0.012 |
| 2011-2016 with no demog. change | -0.163 | -0.174 | -0.174 |
| 2011-2016 All changes | -0.108 | -0.189 | -0.247 |

*The table reports the model-implied cumulative response of output over a 2, 5, and 20 year horizon to a monetary policy surprise shock when the model is calibrated to match Japan for the periods 1980-1985 and 2011-2016. The size of the shock is calibrated to generate a cumulative response of inflation of one percent at the specified horizon. The first row reports cumulative responses using the 1980-1985 calibration. The second row reports results when the production elasticity of substitution is calibrated to 2011-2016 while demographic parameters are kept to 1980s levels. The third row allows for both demographics and elasticity parameters to change to 2011-2016 levels.*

## *Appendix A.4. Alternative model without deep habits*

In this section I consider the implications of aging on the conduct of monetary policy when the elasticity of substitition parameter in households' preferences is directly affected by aging and without deep habit formation. In this setting, population aging will not induce additional persistence in the economy but will nevertheless affect both steady state markups and the slope of the New Keynesian Phillips Curve.

I make two changes relative to the model in the main text. First, in lieu of deep habits, I have the elasticity of substitution as a direct function of age. Second, to allow both the elasticities of substitution for consumption and production using intermediate inputs to directly affect the output cost of disinflationary monetary policy, I assume *Rotemberg* price adjustment costs for both the consumer goods and intermediate inputs layers of production.

*Households*

As in the main text, households are born and die following the *Blanchard-Yaari* overlapping generations framework with an age distribution given by $f(j) = g(1-g)^{j-1} \quad for\ j \in [1,\infty]$. Households choose consumption baskets and labor provision by maximizing the discounted utility from producing and working given by the following program,

$$\begin{aligned}
max \qquad & \mathbb{E}_t \sum_{t'=0}^{\infty} \tilde{\beta}^{t'} U(\{c_{i,j,t+t'}\}, h_{j,t+t'}) && \text{(A.35)}\\
\text{subject to:} \qquad & \\
U \quad = \quad & \frac{x_{j,t}^{1-\sigma}}{1-\sigma} - \frac{h_{j,t}^{1+\kappa}}{1+\kappa} && \text{(A.36)}\\
x_{j,t} \quad = \quad & \left[\int_0^1 c_{i,j,t}^{\frac{\eta_j-1}{\eta_j}} di\right]^{\frac{\eta_j}{\eta_j-1}} && \text{(A.37)}\\
\int_0^1 P_{i,t} c_{i,j,t} di + B_{j,t} \quad = \quad & R_{t-1} B_{j,t-1} + W_t h_{j,t} + \Phi_t \quad \forall t && \text{(A.38)}
\end{aligned}$$

where $\eta_j = \underline{\eta} + (\bar{\eta} - \underline{\eta})(1-s)^{j-1}$ and bonds are in zero net supply.

*Production*

I modify the consumer goods producers' problem relative to the main text by adding *Rotemberg* price rigidities such that consumer goods producers solve the following problem,

$$max \qquad \mathbb{E}_t \sum_{s=0}^{\infty} q_{t+s} \Phi_{i,t+s} \tag{A.39}$$

subject to:

$$\Phi_{i,t} = P_{i,t} c_{i,t} - \int_{m=0}^{1} P_{m,t} Y_{m,t} dm - \frac{\delta_c}{2} P_t c_t \left( \frac{P_{i,t}}{P_{i,t-1} - \pi^*} \right)^2 \tag{A.40}$$

$$c_{i,t} = \sum_{j=1}^{\infty} x_{j,t} \left[ \frac{P_{i,t}}{P_t} \right]^{-\eta_j} f(j) \tag{A.41}$$

$$c_{i,t} \leq y_{i,t} = \left[ \int_{m=0}^{1} Y_{m,t}^{\frac{\gamma-1}{\gamma}} \right]^{\frac{\gamma}{\gamma-1}} \tag{A.42}$$

where $q_t$ is the households' discount factor as before and demand is given by aggregating the solution to the households' problem.

The intermediate goods producers' problem is unchanged relative to the main text (equations 13 to 16). The price adjustment cost parameter is denoted with $\delta_m$ to distinguish it from the price adjustment cost parameter in consumer goods production.

*Aggregation and monetary policy*

I use the same monetary policy rule as in the main text (equation 17). I take the symmetric equilibrium, log-linearize around the zero-inflation deterministic steady state and simplify terms to arrive at the following set of equations characterizing the alternative model.

$$\begin{aligned}
\hat{r}_t &= \rho_r \hat{r}_{t-1} + (1-\rho_r)[\alpha_\pi \hat{\pi}_t + \alpha_y \hat{y}_t] + \varepsilon_{r,t} && \text{(A.43)} \\
\hat{y}_t &= \tilde{\beta}\mathbb{E}_t \hat{y}_{t+1} - \frac{1}{\sigma}(\hat{r}_t - \mathbb{E}_t \hat{\pi}_{t+1}) && \text{(A.44)} \\
\hat{\pi}_t &= \tilde{\beta}\mathbb{E}_t \hat{\pi}_{t+1} + \frac{\tilde{\eta}-1}{\delta_c}\hat{\lambda}_{i,t} && \text{(A.45)} \\
\hat{\pi}_{m,t} &= \tilde{\beta}\mathbb{E}_t \hat{\pi}_{m,t+1} + \frac{\gamma-1}{\delta_m}\hat{\lambda}_{h,t} && \text{(A.46)} \\
\hat{\lambda}_{i,t} + \hat{\lambda}_{h,t} &= (\kappa+\sigma)\hat{y}_t - (1+\kappa)\hat{A}_t && \text{(A.47)} \\
\hat{\pi}_{m,t} - \hat{\pi}_t &= \hat{\lambda}_{i,t} - \hat{\lambda}_{i,t-1} && \text{(A.48)}
\end{aligned}$$

where the age distribution enters through the average elasticity of substitution $\tilde{\eta}$ given by,

$$\tilde{\eta} = \underline{\eta}\frac{g\frac{\bar{\eta}}{\underline{\eta}} + s(1-g)}{g + s(1-g)} \tag{A.49}$$

where as before aging (a decrease in g) lowers the average elasticity of substitution and thus the average price sensitivity of consumers. The steady state markup in this alternative model is given by the following.

$$\mu = \left[\frac{\gamma}{\gamma-1}\right]\left[\frac{\tilde{\eta}}{\tilde{\eta}-1}\right] \tag{A.50}$$

As with the model in the main text, an increase in aging raises steady state markups as well as lowers the slope of the consumer goods price New Keynesian Phillips Curve (equation A.45).

*Calibration and the output cost of disinflation*

I calibrate the model to Japan in the 1980s and 2010s, focusing on population growth, life expectancy, and markups. As there is an extra parameter in this alternative model, I am able to calibrate the parameters such that 10% of the increase in markups is attributed to aging.[35] I then simulate the response of inflation and output to a monetary surprise and calculate the cumulative change

[35] I assume that the two elasticity of substitution parameters are equal in the 1980s and then calibrate the rest of the parameters such that 10% of the increase in steady state markups is due to the change in the consumer elasticity of substitution.

in output given a monetary surprise that reduces inflation by one percent on a given horizon. Table A.9 reports the cumulated response of output across various scenarios.

Table A.9: Response of output to monetary policy surprises

| Horizon | 2 year | 5 year | 20 year |
|---|---|---|---|
| 1980-1985 Baseline | -1.746 | -1.740 | -1.740 |
| 2011-2016 with no demog. change | -5.988 | -5.778 | -5.778 |
| 2011-2016 All changes | -6.708 | -6.238 | -6.236 |

*The table reports the model-implied cumulative response of output over a 2, 5, and 20 year horizon to a monetary policy surprise shock when the model is calibrated to match Japan for the periods 1980-1985 and 2011-2016. The size of the shock is calibrated to generate a cumulative response of inflation of one percent at the specified horizon. The first row reports cumulative responses using the 1980-1985 calibration. The second row reports results when the production elasticity of substitition is calibrated to 2011-2016 while demographic parameters are kept to 1980s levels. The third row allows for both demographics and production elasticity parameters to change to 2011-2016 levels.*

The results indicate that the output cost of disinflation is almost four times larger in the 2010s than in the 1980s. Further, and in contrast to the results in the main text where the model had deep habits, the relative contribution of aging to the increase in the output cost is fairly similar across horizons at about 10% which is also the share of the increase in markups attributed to aging.

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