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Abstract

How does the population age structure affect monetary policy? With advanced economies experiencing increased inflation risk and sluggish growth, it is more important than ever to understand how the monetary toolbox transmits to the outcomes that policymakers wish to affect. Studying a long run panel of countries, we identify the impact of changing population age structures on the effectiveness of monetary policy transmission to the economy. These shocks are identified using a recently proposed *trilemma* instrument for quasi-exogenous change in policy rates. On the one hand, we provide strong empirical evidence for a relationship between age structure and the transmission of interest rate shocks to CPI inflation, with young populations reducing this transmission, middle-aged ones reinforcing it, and older retirees strongly reducing it again. We observe the same pattern for nominal wages and real house prices. On the other hand, population aging is found to have transitory effects on the responsiveness of real aggregate variables such as, output, consumption, and investment with older populations delaying the impact of monetary policy. We find no impact on transmission to unemployment. These results have potentially important implications for the conduct of policy, particularly in the current environment where central bankers must frequently choose between their inflation and full employment targets.

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1. Introduction

Advanced economies are getting old and so are their policy instruments. Understanding the interaction between the tools of macroeconomic policy and underlying demographics will be a crucial question in the coming decades as populations continue to age. The return of heightened inflation risk, along with slow recovery from both the global financial crisis and COVID-19 pandemic, makes understanding factors that alter policy transmission ever more important. The outsized boomer cohort currently straddles retirement and will progress ever further into old-age groups. Meanwhile, trends in fertility and longevity continue to push weight toward the end of the age distribution, inverting the traditional population pyramid. Existing work finds that households may have differential exposure to interest rate changes over the life-cycle, suggesting a potential channel through which demographics alter the transmission of policy rates to aggregate outcomes.

In this paper, we use long run data from seventeen advanced economies to study the heterogeneous impact of quasi-exogenous monetary policy shocks as population weights shift. We find that there is a potentially large impact of age-structure on prices (CPI inflation, wages, and house prices), with young and old age groups reducing the effectiveness of policy, and prime age workers increasing policy transmission. We find that aging has a potentially transitory impact on monetary policy transmission to real aggregate output, consumption, and investment-to-GDP, with demographics only affecting transmission in the first and second year after a monetary policy shock. Here older populations delay transmission, but have no long term impact. We find no evidence of impact on unemployment transmission at any horizon. In the face of stagflation risk, our results provide one point of suggestive evidence that graying populations in advanced economies may create scope for central banks to more aggressively pursue their full employment mandates as demographics weaken the negative side-effects of such policy on their inflation objectives. However, such results also suggest that traditional interest rate tools may have less power to fight existing inflation than they did during the period of the Great Moderation, a period that conspicuously lines up with the boomer cohort's presence in the workforce.[1]

A large literature investigates heterogeneity of monetary policy impact. Bilbiie (2018) provides an analytical framework for thinking about this heterogeneity in the context of macroeconomic models. A key insight of this work is that income constrained households will react differently than unconstrained agents in the face of a monetary policy change, opening a door for differential effects as cyclical variations make households more or less constrained. Eichenbaum, Rebelo, and Wong (2022) provide similar insight, while

[1]The youngest boomers turned 18 in 1982 while the oldest boomers turned 65 in 2011. One could consider this window the period when (roughly speaking) the entirety of the boomer cohort was of working age.

documenting that younger households are more constrained and therefore have stronger consumption responses to interest rate shocks. They use a life-cycle model with constrained mortgage financing to show that liquidity constraints affect the transmission of monetary policy. Such a model predicts much lower consumption responses in the face of monetary policy as populations age as a larger share of households leave this constrained group. Another large literature studies the importance of increased savings leading up to retirement, which may itself affect growth and interest rates.[2] Kopecky and Taylor (2022) find that household life-cycle investment decisions also involve significant portfolio reallocation both as households age and in response to these endogenous movements in long run real rates, a channel which may also affect monetary transmission.

We adopt a methodology developed by Cloyne, Jordà, and Taylor (2020), who implement a Kitagawa-Blinder-Oaxaca[3] (KBO) decomposition in a local projections (Jordà, 2005) estimation. More recently this method has been applied to the context of monetary policy, with Alessandri, Jordà, and Venditti (2025) using it to show the impact of financial markets on monetary transmission. Our policy shocks are identified using quasi-random interest rate shocks developed by Jordà, Schularick, and Taylor (2020). These leverage constraints on policy due to the Trilemma to identify exogenous shocks to interest rates. Because pegged countries are not fully able to set domestic policy, they may be hit with shocks stemming from unexpected movements in their base country policy rates. An advantage of this methodology for our series is that we are able to make use of the long run macro-history data of Jordà, Schularick, and Taylor (2017), which covers a panel of advanced economies going back as far as 1870. Given the slow moving nature of demographics it is valuable to be able to conduct analysis over a window large enough for demographic movements to play out. In particular, we are generally able to observe substantial period before the entry of the large and historically unique baby boomer cohort into the labor force.

There is a growing field of research on inflation related to aging. Bobeica, Nickel, Lis, and Sun (2017) find a positive effect of the growth rate in the working age population on inflation using a cointegrated VAR approach in the US and euro area. Similar results are found in de Albuquerque, Caiado, and Pereira (2020) using a panel cointegration method and 24 countries with the age 35-64 group creating disinflationary pressure while very old population groups (over 75) appear to contribute strongly to inflation. Aksoy, Basso, Smith, and Grasl (2019) find as well that aging will be inflationary with a negative effect for the working age population groups and positive effects for dependents. In work closely related to this paper, Juselius and Takáts (2021) estimate the population-age inflation relationship

[2]See for example: Gagnon, Johannsen, and Lopez-Salido (2021), Eggertsson, Mehrotra, and Robbins (2019), and Auclert, Malmberg, Martenet, and Rognlie (2021).

[3]See: Kitagawa (1955), Blinder (1973), and Oaxaca (1973).

on the same panel of developed economies. Unlike their work we focus on the transmission mechanism. Specifically, we look not only at the direct effect of age on inflation, which we will see, but also on how it *transmits* through policy.

We directly contribute to a small but growing literature emphasizing the importance of population age structure on the transmission of monetary policy. Berg, Curtis, Lugauer, and Mark (2021) show that consumption response to monetary policy differs across age groups with old-age households increasing their consumption substantially in response to a monetary policy rate cut, with much smaller (even negative) and statistically insignificant impacts on other age groups. Curtis, Garín, and Lester (2024) explore differences in elasticity of substitution, finding that younger age cohorts exhibit higher elasticities, flattening the Phillips curve as economies age. Eichenbaum, Rebelo, and Wong (2018) show that monetary policy can work to lessen the collateral constraints, which bind relatively strongly for younger workers. They find that young households who are relatively credit-constrained will be affected more from monetary shocks. This leads to quantitatively large effects and would lead to a dampening of monetary transmission as populations age. Similar mechanisms are explored empirically in Kronick and Ambler (2019) who discuss both these credit and risk channels, but also a wealth channel that could potentially work in the other direction as older populations have more households with accumulated wealth who may respond more to changes in interest rates. They study this effect in a panel of Canadian provinces. They suggest that aging populations have acted to minimize the effect of monetary policy on inflation, though they find some mixed results. Recently Leahy and Thapar (2019) use variation across US states to identify the effect of age structure on monetary transmission. They find the proportion of middle aged individuals is important for increasing the responsiveness of monetary policy shocks. Below we present findings that are broadly consistent with this literature with young age groups dampening transmission to policy, middle aged groups increasing it, and the elderly reducing it once again.

While we discuss potential mechanisms underlying our findings, this paper does not develop a formal macroeconomic model to explicitly capture them. Instead, our analysis provides empirical evidence that aligns with some of the mechanisms proposed in the literature while contrasting with others. In particular, while the channel emphasized by Eichenbaum et al. (2022) is compelling, our results suggest that additional mechanisms—especially those affecting older workers and retirees—may play an important role. Our finding that middle-aged individuals strongly reinforce monetary transmission is consistent with Leahy and Thapar (2019), who show, using high-frequency identification of U.S. monetary policy shocks, that employment and income responses are weaker in populations with a larger share of individuals under 35, and stronger where the share of those aged 40–65 is higher. We uncover similar evidence regarding the effect of monetary policy on inflation, though we also find a subsequent weakening for retirees, limited and short-lived effects on output, and negligible impacts on employment. Finally, Mangiante (2024) also examine the interaction between monetary policy pass-through and population aging in the U.S., showing that demographic trends can amplify the output responsiveness of monetary policy due to the varying composition of consumption baskets over the life cycle.

The paper proceeds as follows. In section 2, we discuss the data and our methodological approach. section 3 presents results of the OLS and IV estimations for the response of inflation and output to changes in interest rates. We further explore some potential mechanisms by estimating the responses of nominal wages, unemployment, consumption, investment, and real house prices in section 4. section 5 concludes.

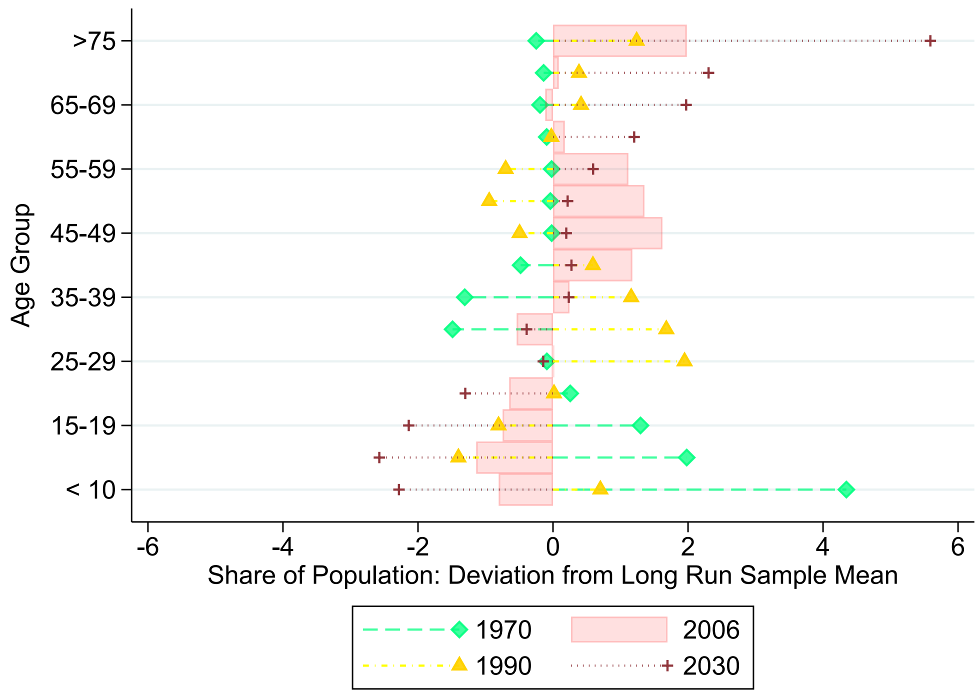
2. Data and Empirical Strategy

2.1. Data

Our population data are drawn from the Human Mortality Database Human Mortality Database (2019), which provides detailed information on the age structure of populations over extended historical periods—though coverage does not reach the 1870 starting point of our macroeconomic dataset for all countries. To extend the U.S. series back to 1900, we supplement these data with figures from the U.S. Census National Intercensal Tables. We construct two primary measures of population age by calculating five-year population age shares across the life cycle, along with two broader groups for children under 10 and individuals aged 75 and above. To illustrate the type of demographic variation that underpins our analysis, we visualize these demeaned population age shares for the United States in Figure 1. These measures will subsequently serve as the basis for a set of demographic controls, described in greater detail in subsection 2.5.

There are three notable demographic forces at work throughout this sample. The first two are long run trends: declining fertility and rising longevity. These work together such that over time there are, generally, fewer young cohorts and much larger shares of old age individuals in the population. The third, and quite large, factor is the recent evolution of the baby boomer cohort through the population. This cohort, born between 1946 and 1964 represented a particularly large increase in fertility, which combined with rapid increases in longevity has seen an outsized impact through population pyramids in most developed countries. The size and timing of this boom, and the echo boom that followed, creates a great deal of variation both across countries and over time. So too do large differences in

Figure 1: *United States Age Shares: Deviation from Long Run Mean*



the rate of decline of fertility and mortality.

This demographic data is merged with Jordà et al. (2017) (JST), who provide a rich dataset of macroeconomic variables, which we use as outcome variables, as well as other controls. With the addition of Jordà, Knoll, Kuvshinov, Schularick, and Taylor (2019) there are also a large number of financial variables we include in some specifications. Our estimates utilize 17 of the countries contained in this dataset, going back as far as 1870 up to 2006, where we cut of our sample to avoid the turbulent period around the global financial crisis. This also allows for ease of comparison of our direct monetary policy estimates with Jordà et al. (2020). Shortening our sample in this way has no impact on the significance or economic interpretation of nearly all of our results, and for all but one outcome (real house prices) the estimates we report in the paper are simply more conservative versions of those that make use of the full JST sample. We discuss this further in Appendix B.

2.2. Estimation Strategy

There are two primary challenges to estimating conditional policy transmission. The first, is a standard identification of the policy itself. To overcome this, we use an instrumental variables approach suggested in Jordà et al. (2020), which exploits quasi-exogenous changes in domestic policy in pegged economies following changes in base country policy rates due to the well known *trilemma* in international macroeconomics. The second challenge is to decompose policy estimates conditional on various age structures. To accomplish this we adopt a decomposition method common in the microeconomic literature, originally developed by Kitagawa (1955), Blinder (1973), and Oaxaca (1973) (KBO). Applying this KBO method to empirically estimated impulse response functions (IRFs), estimated via local projections (LPs) is demonstrated in Cloyne et al. (2020).

2.3. Monetary Policy Instrument: The Trilemma

We identify quasi-exogenous changes in monetary policy using the trilemma instrument developed in Jordà et al. (2020). The long standing theoretical and empirical regularity that pegged countries face limited monetary policy autonomy while maintaining open capital markets creates quasi-exogenous movements in policy rates when the base country to which they peg their currency makes unexpected changes to their policy rates. Their approach suggests utilizing base country changes in interest rate policy for pegged countries. Denoting the base country as $b(i,t)$ of pegging country i in time t, they define an instrument for domestic policy changes as:

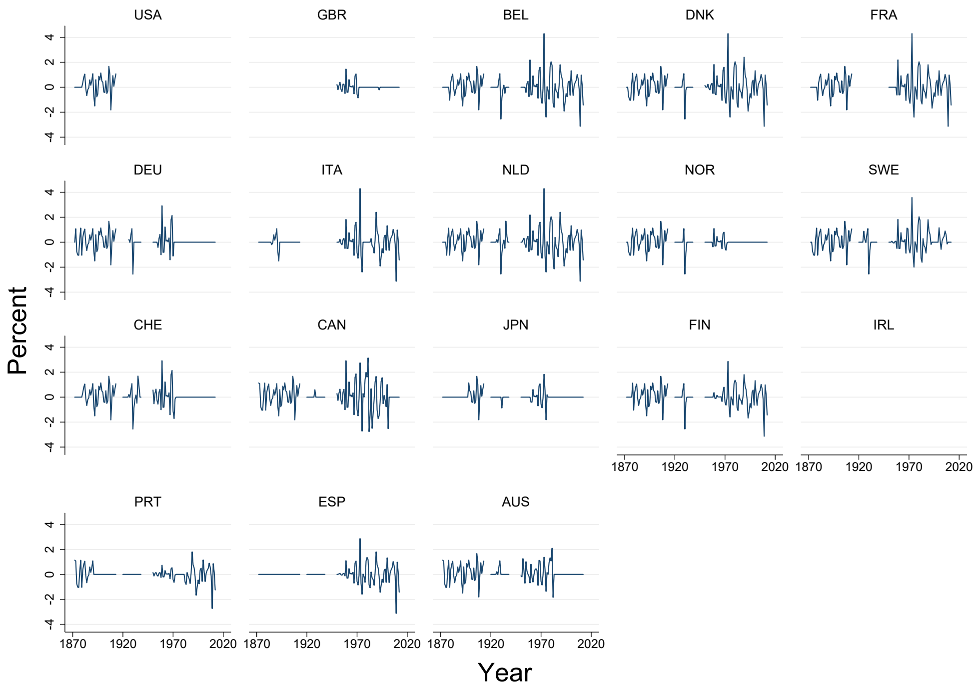
$$z_{i,t} = k_{i,t}\left(\Delta r_{b(i,t),t} - \Delta \hat{r}_{b(i,t),t}\right)$$

where $k_{i,t}$ is a measure of the pegging country's capital openness, and $r_{b(i,t),t}$ interest rates in the base country. The term $\Delta \hat{r}_{b(i,t)}$ are changes in the base country interest rate that are predictable by observables in the base country using current and lagged macroeconomic controls, as well as lagged values of the policy variable itself. Finally, note that $z_{i,t} = 0$ if the country is not engaged in a fixed exchange regime. To ensure credibility of the current peg regime, Jordà et al. (2020) require that the country be pegged both in the current year and the year prior to qualify. Local average treatment effects are only causally identified by this trilemma shocks for pegs as the instrument does not operate for floating exchange rate economies. As such in all estimations below we restrict the sample to pegging countries as in Jordà et al. (2020).

To get a sense of how this instrument looks across our panel, we plot the values for each country in the JST database in Figure 2. As can be seen from this figure the instrument is not available for Ireland in their data[4] so while the Macrohistory database contains 18 variables our estimations will be on this 17 country subsample.

[4]Ireland has been quite recently added to the JST database.

Figure 2: *JST Trilemma Instrument*



2.4. Estimating Equations

The primary object of interest are the cumulative impulse response functions for the change in output and inflation as a result of monetary shocks. These are computed using the local projections method of Jordà (2005). To do this for the standard average effects (those without heterogeneity), we estimate the set of impulse responses as below:

$$y_{i,t+h} - y_{i,t-1} = \mu_t^h + \Delta r_{i,t}\beta^h + (x_{i,t} - \bar{x})\gamma^h + D_{i,t}\gamma_d^h + \epsilon_{i,t+h}\ ; \quad for\ h = 0, \dots, H. \tag{1}$$

This specification is similar to Jordà et al. (2020), who study monetary policy effects. Unlike their work we include the term $D_{i,t}$, which represents the set of controls for population age structure. Additionally to follow the KBO interpretation all controls (including demographic controls) are included as their value relative to the sample mean. Equation 1 does not itself allow for heterogeneous effects. To compute these we instead estimate the following equation:

$$\begin{aligned} y_{i,t+h} - y_{i,t-1} = \mu_t^h + \Delta r_{i,t}\beta^h + (x_{i,t} - \bar{x})\gamma^h + \Delta r_{i,t}(x_{i,t} - \bar{x})\theta^h \\ + D_{i,t}\gamma_D^h + \Delta r_{i,t} D_{i,t}\theta_D^h + \epsilon_{i,t+h}\ ; \quad for\ h = 0, \dots, H. \end{aligned} \tag{2}$$

The estimating equation in Equation 2 follows the procedure outlined in Cloyne et al.

(2020), who describe in detail the validity of the KBO style decomposition in an LP framework. Having calculated the impulse responses function with this series of equations we obtain a direct effect of interest rate changes on outcomes at any horizon h with β^h, as in the standard LP. However, now we also have the *indirect effect* of a change in any of the covariates through the interaction term, θ^h. Thus the impact of demographics on the *transmission* of monetary shocks to a particular outcome of interest is estimated by the parameters θ_D^h, which we split out from the remaining covariates for clarity, but enters in principle identically to other controls in a naive OLS estimation of Equation 2. The estimates of the γ^h terms give the composition effects. That is those effects of a given set of covariates on the outcome unrelated to interest rate shocks. We also include two lagged values of demographic variables, the dependent variable, lagged policy, and a measure of aggregate GDP growth[5] to control for global time trends. Time fixed effects would require a large number of additional parameters and may introduce bias if there are independent country-specific time trends. As in Jordà et al. (2020) we also allow for each variable to have a separate coefficient for the period from 1973-1980 (inclusive) to resolve the well-known "price puzzle" that arises when estimating interest rate change impacts on inflation.

This specification is convenient in that it handles empirical estimation of state dependence of estimated policy effects in a straightforward way. Much of the literature estimating such effects will opt to estimate coefficients on split samples.[6] We emphasized that this KBO estimation is not a magic wand for identification. In principle, for a causal interpretation of these indirect effects one should have a defensible identification strategy for *both* the policy shock, and for the interactive control as any endogeneity via other regressors could contaminate results. We use the Trilemma instrument of Jordà et al. (2020) to generate plausibly exogenous movements in interest rates due to countries being constrained by their exchange rate policy.

Our preferred estimates will use the Jordà et al. (2020) trilemma instrument described above as a means of identifying quasi-exogenous variation in interest rates. Our IV estimates will be obtained by estimating:

$$\begin{aligned} y_{i,t+h} - y_{i,t-1} = \mu_t^h + \widehat{\Delta r}_{i,t}\beta^h + (x_{i,t} - \bar{x})\gamma^h + \Delta r_{i,t}(x_{i,t} - \bar{x})\theta^h \\ + D_{i,t}\gamma_D^h + \widehat{\Delta r_{i,t} D}_{i,t}\theta_D^h + \epsilon_{i,t+h}\,; \quad \textit{for } h = 0, \ldots, H, \end{aligned} \tag{3}$$

where $\widehat{\Delta r}_{i,t}$ and each demographic control contained in $\widehat{\Delta r_{i,t} D}_{i,t}$ use predicted values using a two-stage least squares (2SLS) approach. For all specifications below we populate $x_{i,t}$

[5] Here we take the growth of aggregate GDP of the 17 countries within sample.

[6] See for example many papers on state dependent fiscal multipliers, for example Ilzetzki, Mendoza, and Végh (2013).

with contemporaneous values and two lags of the log change in consumption and the log change in investment.[7] These also appear in first stage estimations of the 2SLS equation. The coefficients on the *direct* and *indirect* demographic coefficients and on the average policy treatment are nearly identical to estimates that include an additional first stage estimate for the contemporaneous values of these as $\widehat{\Delta r_{i,t} X_{i,t}}$, or indeed to specifications that drop all additional controls entirely.[8] The 2SLS estimates of Equation 2 will have a first stage equation for $\Delta r_{i,t}$ as well as for $\Delta r_{i,t} D_{i,t}$, each of the interactions with population age variables given by:

$$\begin{aligned}\Delta r_{i,t} &= z_{i,t} b + z_{i,t} D_{i,t} \tau + \Delta r_{i,t} (x_{i,t} - \bar{x}) \tau_x + (x_{i,t} - \bar{x}) g + \eta_i \\ \Delta r_{i,t} D_{i,t} &= z_{i,t} b_d + z_{i,t} D_{i,t} \tau_d + \Delta r_{i,t} (d, x_{i,t} - \bar{x}) \tau_x + (x_{i,t} - \bar{x}) g_d + \eta_{d,i}.\end{aligned} \tag{4}$$

2.5. Controlling for Population Structure: an Augmented Fair and Dominguez (1991) Methodology

Not wanting to impose assumptions on the importance of individual age groups a priori, a naive regression might include a large number of population age shares into Equation 2 directly. Doing so poses three problems. The first, is that such an approach may add significant parametric burden to the model specification, reducing power. The second is that the full set of population shares is inestimable along with a regression constant as they are perfectly collinear. Finally, with small age groupings population age shares become increasingly collinear with neighboring age groups. This creates substantial instability of estimated parameters, with estimated signs often reversing from one group to the next. The solution to these problems is to fit estimated regression coefficients with a low-order polynomial, first suggested in Fair and Dominguez (1991). To do this requires two assumptions:

1. Denote α_j, the regression coefficient on population share $p_{j,i,t}$ of age group j in country i and time t. Assume that all of the effects of these coefficients across the age distribution sum to zero. In other words:

$$\sum_{j}^{J} \alpha_j = 0$$

2. Assume that the age coefficients α_j can be fitted with a K order polynomial. In other

[7] Except when these are the outcome of interest in section 4.

[8] We chose initially to keep this approach close to that of Jordà et al. (2020), who use these controls as well as additional financial variables. We keep these and not financial controls as inclusion of the latter drop a significant fraction of the estimation sample.

words:

$$\alpha_j = \sum_{k}^{K} \gamma_k j^k \tag{5}$$

The first point is about feasibility of estimating effects of J perfectly collinear terms along with a regression constant. The second smooths estimated coefficients by age, while also reducing the number of parameters required. The amount of life-cycle variation allowed is determined by the k order of the polynomial, as there may be as many as $k-1$ turning points in the estimated parameters by age. Keeping with the KBO estimation above we use demeaned population shares, rather than the shares directly. By putting these deviations of population age shares from long run means into Equation 1, and applying the two assumptions above we construct demographic variables that estimate the γ_k parameters of the fitted polynomial. These demographic controls are given by:

$$Dk_{i,t} = \left[\sum_{j}^{J} (p_{j,i,t} - \bar{p}_{i,t}) j^k \right]. \tag{6}$$

For our baseline results we use a $k = 3$ third-order polynomial, constructing $D_1 - D_3$ age structure variables. For a detailed derivation of Equation 6, as well as a discussion of the Fair and Dominguez (1991) see subsection A.1. We also motivate our choice of $k = 3$ and show that it has little qualitative impact on our estimates in subsection A.2.

3. Results

We present our results from both OLS and IV estimates of Equation 2 and Equation 3 below. To simplify the discussion of the population age dependent impulse responses, we begin with two key outcome variables of interest: inflation and output growth. Our estimates suggest that the transmission of interest rate policy to inflation may be particularly sensitive to the age distribution, while there is little correlation between population age structure and the transmission of interest rate shocks to output.

3.1. Inflation Response

We start by showing the impact of population age structure on the response of inflation to policy rate changes. Table 1 reports the OLS and IV estimates of the cumulative response of inflation to a percentage point change in interest rate at five annual horizons. The IV specification finds an average effect of the interest rate shock (β^4) after five years of -3.82, suggesting that each percentage point increase in the policy rate on average leads to a nearly four percentage point decline in inflation. This is somewhat larger than the -3.18 estimate in Jordà et al. (2020) using the same instrument. This is largely due to our choice to limit our control set in favor of a larger sample size.[9] As in Jordà et al. (2020) OLS estimates of this direct effect are relatively weak and with some positive signs. For all estimates we report Cragg and Donald (1993) F-statistics (C-D F) as well as a Sanderson and Windmeijer (2016) multivariate F (S-W F). Since the S-W F-statistic is calculated at each first stage for our endogenous regressors, and here we have four, we only report the minimum of these F-statistics.

Table 1: *Response of Inflation to Interest Rate Changes*

	OLS					IV				
Horizon, h	0	1	2	3	4	0	1	2	3	4
Δr_t	0.23***	0.39**	0.21	-0.10	-0.30	-0.29	-0.86†	-1.55**	-2.84***	-3.82***
	(0.07)	(0.17)	(0.20)	(0.23)	(0.32)	(0.31)	(0.55)	(0.66)	(1.00)	(1.40)
D1	-0.00	1.01	3.19*	6.41**	9.14**	-0.16	0.72	2.87*	6.14***	8.99***
	(0.54)	(1.03)	(1.77)	(2.66)	(3.76)	(0.55)	(0.96)	(1.50)	(2.18)	(3.06)
D2	-0.74	-3.66†	-8.90**	-15.43**	-21.26**	-0.48	-3.19	-8.39**	-15.06***	-21.16***
	(1.18)	(2.14)	(3.60)	(5.58)	(7.61)	(1.29)	(2.30)	(3.55)	(5.20)	(6.87)
D3	0.46	1.98†	4.54**	7.54**	10.16**	0.31	1.73	4.26**	7.32**	10.04***
	(0.62)	(1.14)	(1.88)	(2.91)	(3.87)	(0.70)	(1.31)	(1.99)	(2.90)	(3.73)
$\Delta r_t \times D1$	-0.05**	-0.06	-0.04	0.02	0.04	0.09	0.24	0.39†	0.73**	1.03**
	(0.02)	(0.04)	(0.05)	(0.07)	(0.10)	(0.10)	(0.19)	(0.24)	(0.34)	(0.46)
$\Delta r_t \times D2$	0.07**	0.08	0.07	-0.03	-0.07	-0.18	-0.49	-0.78*	-1.43**	-1.97**
	(0.03)	(0.06)	(0.09)	(0.11)	(0.16)	(0.19)	(0.34)	(0.43)	(0.59)	(0.79)
$\Delta r_t \times D3$	-0.03*	-0.03	-0.03	0.02	0.03	0.09	0.23†	0.38*	0.68**	0.93***
	(0.02)	(0.03)	(0.04)	(0.05)	(0.07)	(0.09)	(0.16)	(0.20)	(0.27)	(0.36)
$X_{i,t}$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
$X_{i,t}\Delta r_t$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cty FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
C-D F	-	-	-	-	-	13.82	13.82	13.82	13.82	13.82
min S-W F	-	-	-	-	-	23.94	23.94	23.94	23.94	23.94
R^2	0.71	0.73	0.74	0.73	0.69	0.68	0.69	0.70	0.67	0.63
N	932	932	932	932	932	932	932	932	932	932

Table reports estimations of IRFs of CPI Inflation to a one percentage point interest rate change, and third order polynomial demographic controls. Clustered standard errors (country level) are in parenthesis with $\dagger p < 0.15, *p < 0.10, **p < 0.05, ***p < 0.01$ significance. Additional controls in $X_{i,t}$ are: log real consumption and log real investment per GDP. Regressions include two lags of the dependent variable as well as two lags and contemporaneous values of all additional controls. All controls are demeaned and interacted with interest rates as well as a dummy for 1973-1980 to account for the well documented "price puzzle." Cragg-Donald F-tests for weak instruments are reported as well as the minimum value among Sanderson-Windmeijer multivariate F-tests. Variables D2/D3 are scaled by 10/100 for readability.

[9] We note that their estimates cover the same period, but have 639 observations, to our 932. This appears to be due to the inclusion of a rich set of financial controls including: short and long interest rates, house prices, stock prices, and credit-to-GDP ratios. While we see these as potentially important they are frequently missing early in the sample which we view as important for capturing long run demographic variation.

Population age structure has quite strong, and relatively consistent *composition* effects on cumulative inflation. These are the γ_D terms that estimate the empirical relationship between age structure and cumulative inflation directly. Only in the IV estimation there are significant estimates of the *indirect* effect of demographics, those that are interacted with interest rate shocks.

The polynomial demographic controls estimated as in Fair and Dominguez (1991) are difficult to interpret on their own. The coefficient on $D1$, for example, is the coefficient on the linear term of the polynomial that fits the five-year age specific coefficients described in Equation 5. Of greater interest are the actual α_j coefficients of each individual age, which can be backed out by using these regression parameters in Equation 5. These are presented for the full $h = 4$ horizon in Figure 3 for both *direct* effects (with standard errors calculated via the delta method) and for the *indirect* effects, which are conditional on a one standard deviation change in interest rates (as they are by construction zero if $\Delta r_{i,t} = 0$).

The age specific coefficients in Figure 3a show that impact of increasing a particular population age share one percentage point above its mean value in the sample. These *composition* effects are large, but demographic changes are small and slow moving, usually within a few percentage points of the long run mean. Because the data is demeaned, population age shares must sum to zero, so increases in one ages may be at least partially offset by the necessary movements in others. Notably these estimates suggest that early career workers are broadly inflationary while middle-to-late career workers provide deflationary pressure. This is slightly out of sync with recent work by Juselius and Takáts (2021), who much strong inflationary effects for late career workers and retirees. Our estimates are not perfectly comparable, as theirs are not dynamic estimates, but other work with dynamic estimates and a similar specification finds estimates quite close to theirs (Kopecky, 2023a). We thus suspect that it is the inclusion of monetary policy transmission itself that primarily alters this direct effect. While this is not our object of interest it may be important to understand policy-demographic interactions to properly estimate an age-inflation relationship directly.[10]

The *indirect* effects in Figure 3b need not sum to zero and are here positive for all but a few age groups. However, what matters is not the sign of a given age coefficient, but the relative difference between them as the deviations of population age shares from their mean in any given year are themselves still sum to zero. The large positive impact of ages

[10]Both Juselius and Takáts (2021) and Kopecky (2023a) use a fourth order polynomial, this is not the source of differences in our estimates. We show in subsection A.2 that we find find broadly consistent, and significant effects of fourth order coefficients here, but there is concern of strong *overfitting* of age coefficients in such specifications, which have qualitatively similar impulse response functions, but more extreme swings in the oldest age group.

15-24, which offset the negative mean impact of the interest rate shock, suggest that large population weights in young dependents and early career workers may weaken the impact of interest rate policy. These indirect coefficients are much smaller for middle and late career age groups. Thus moving population weights from early career to late will reduce the overall impact of policy and work to reinforce the negative average effects.

The large boomer cohort rides this wave. Aged between 6 and 24 in 1970 they have large weights in relatively low coefficients of young dependents, but are starting to firmly enter early career. In 1990 this cohort is between 26 and 44, putting a large amount of weight on these relatively high early career coefficients. On the eve of the global financial crises the boomers are firmly in the trough of this figure, and reduce this (negative) effect further. Projecting forward the boomers, now mostly retired will continue to add to old age groups, whose strong positive effect would reduce transmission.

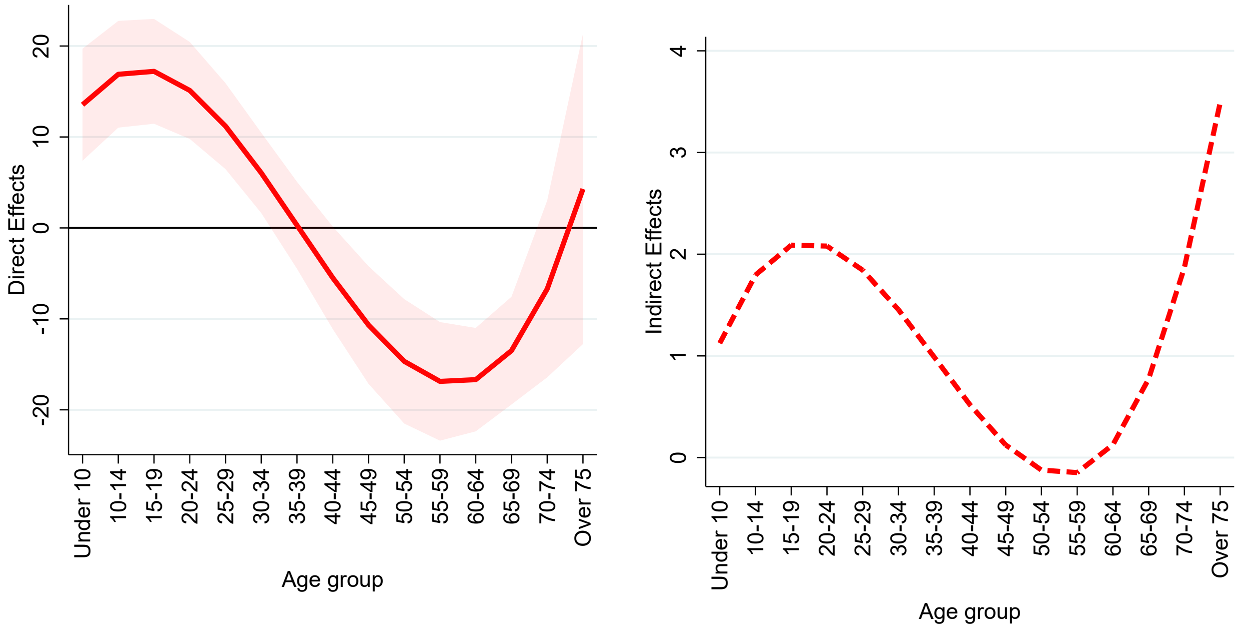
While the story of the boomer cohort is the most critical for understanding the last fifty years of demographics in advanced economies, there are other demographic forces at work. There is an echo boom caused by this large cohort entering childbearing years, and continuing long run trends in falling fertility and mortality that continues to shrink the share of young dependents while increasing the relative shares of older dependents. The most complete way to understand our estimates is to calculate the *conditional* impulse response functions for a particular age distribution relative to the average effect. We plot a number of examples of such conditional IRFs in Figure 4.

The conditional IRFs in Figure 4 provide an easier way to visualize how these population weights interact a particular set of age-specific coefficients. Figure 4 shows the estimated impact of interest rate shocks on average as well as the effect conditional on the 1970, 1990, 2006, and estimated 2030 populations for three countries: the United States, France, and Denmark.

We choose Denmark in particular because unlike the other two countries it is pegged for all of the years shown and therefore all but the projected 2030 demographics are in-sample estimates. To help understand what drives these conditional responses we also plot the demeaned population age shares on the right-hand side of this figure for each of these countries and a number of years. As expected from the discussion above, the transmission of monetary policy is relatively weak as the large boomer cohort is in early-to-mid career from 1970-1990 in the United States. These estimates suggest that there would be strong estimated demographic effects reinforcing the effects of interest rate changes on the eve of the global financial crisis in 2006. It must be kept in mind that other factors may also matter for policy impact and that our estimates do not make any attempt to estimate the size of policy multipliers in this year, but rather to understand if population age is reinforcing, or

Figure 3: *Age Specific Estimates at H = 4: Composition + Indirect Age Coefficients*

(a) *Age Specific Coefficients: Composition Inflation Effect* **(b)** *Age Specific Coefficients: Indirect Inflation Effect ($+\sigma\Delta r_t$ Shock)*



counteracting these policies.

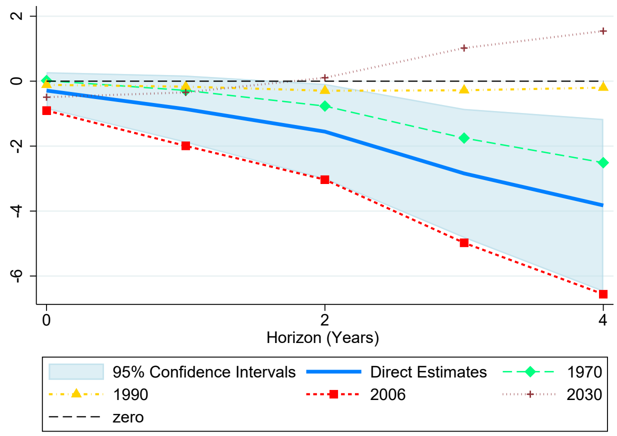
Projecting forward suggests that the oldest age group, with outsized increases in their share of population and in estimated impact in Figure 3b will dominate and provide puzzlingly large positive estimated conditional IRFs by 2030. These should be taken cautiously for two reasons. For one, as mentioned above these estimates do not make an attempt at identifying causal variation in population age, a task that may be challenging in this context. Second, the Fair and Dominguez (1991) approach is prone to overfitting the age-specific coefficients, particularly at the beginning or end of the distribution. Since this single age group singularly drives this large reversal in estimated policy effects they should be taken with a grain of salt.

3.2. Output Response

We now turn to the output response, measured as the cumulative log change in real GDP. The average effects are broadly consistent with those reported by Jordà et al. (2020), who, using a similar instrument and sample of countries, estimate an impact of interest rates of -2.57 at the $h = 4$ horizon. Unlike the results for cumulative inflation, we find no evidence of *composition* effects, and the *indirect* effects identified here appear to be short-lived. In particular, we estimate significant demographic interactions at the one- and

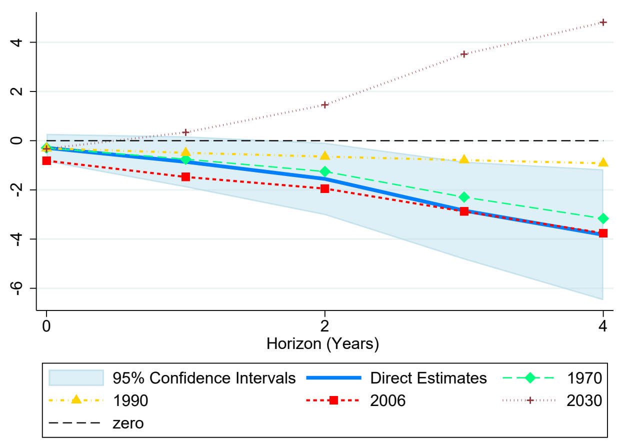
Figure 4: *Inflation Response to Interest Rate Shock, KBO Decomposition: Full Age Controls*

(a) *Conditional IRF: United States*

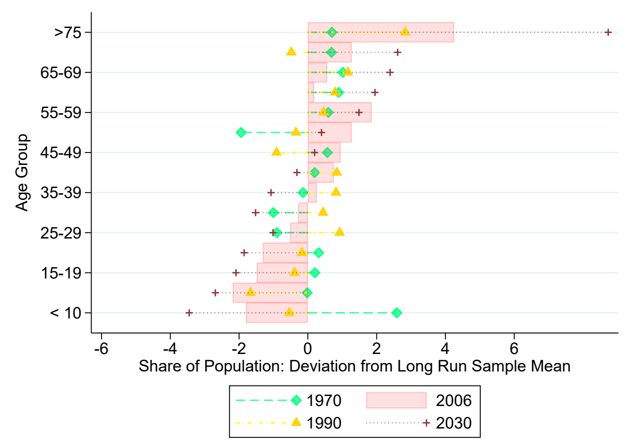


(b) *Population Shares: United States*

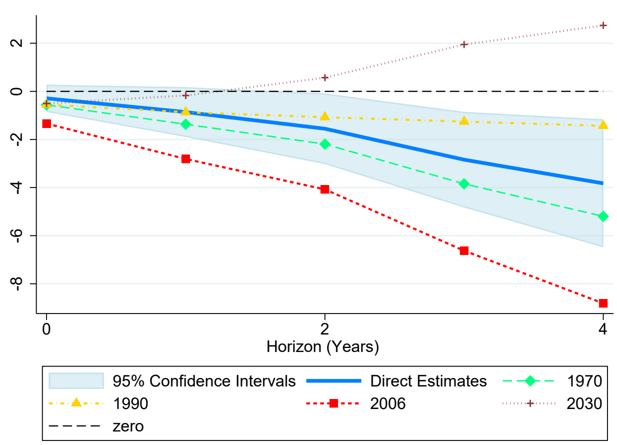
(c) *Conditional IRF: France*



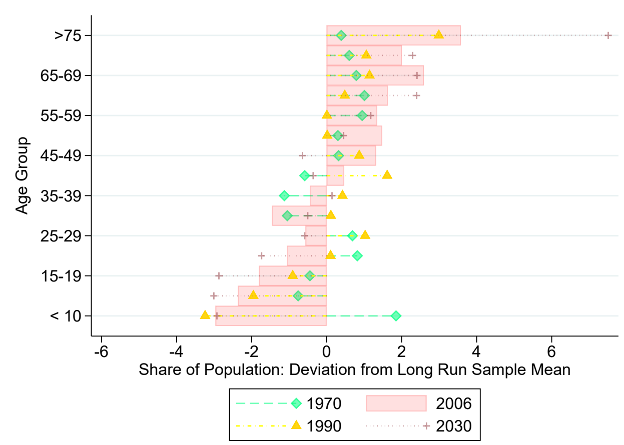
(d) *Population Shares: France*



(e) *Conditional IRF: Denmark*



(f) *Population Shares: Denmark*



Notes: Direct estimates are the average estimate of a one percentage point interest rate changes on inflation when population is at long run sample mean. Conditional IRFs are estimated effects of interest rate shocks conditional on age distribution of each country in a given year.

two-year horizons.

Table 2: *Response of Output to Interest Rate Changes*

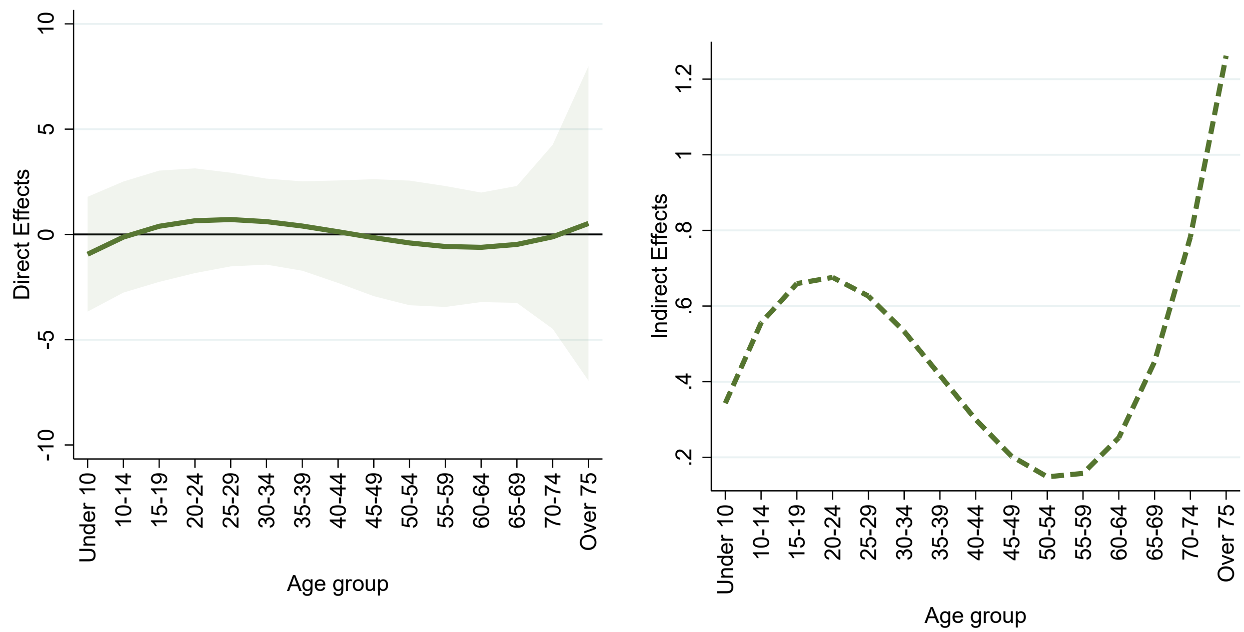
	OLS					IV				
Horizon, h	0	1	2	3	4	0	1	2	3	4
Δr_t	0.13***	-0.29***	-0.51***	-0.50**	-0.18	0.07	-1.31***	-2.80***	-2.65**	-2.86**
	(0.03)	(0.09)	(0.15)	(0.18)	(0.21)	(0.16)	(0.37)	(0.81)	(1.05)	(1.25)
D1	0.09	1.40	2.45	2.25	3.05	-0.06	0.92	1.35	0.83	1.17
	(0.35)	(1.19)	(1.91)	(2.41)	(3.07)	(0.31)	(1.19)	(2.03)	(2.47)	(3.18)
D2	0.33	-1.84	-3.93	-3.46	-4.64	0.60	-0.99	-1.98	-0.95	-1.31
	(0.77)	(2.27)	(3.73)	(4.32)	(5.11)	(0.69)	(2.27)	(4.00)	(4.51)	(5.40)
D3	-0.29	0.63	1.70	1.33	1.66	-0.41	0.24	0.79	0.17	0.13
	(0.39)	(1.08)	(1.81)	(2.03)	(2.29)	(0.35)	(1.08)	(1.95)	(2.15)	(2.47)
$\Delta r_t \times D1$	0.01	0.01	0.03	-0.04	-0.10	-0.02	0.12**	0.31**	0.16	0.07
	(0.01)	(0.03)	(0.05)	(0.06)	(0.07)	(0.04)	(0.06)	(0.15)	(0.22)	(0.29)
$\Delta r_t \times D2$	-0.01	-0.03	-0.06	0.02	0.14	0.05	-0.23**	-0.57*	-0.33	-0.15
	(0.02)	(0.06)	(0.09)	(0.11)	(0.12)	(0.08)	(0.11)	(0.29)	(0.45)	(0.60)
$\Delta r_t \times D3$	0.00	0.01	0.03	0.00	-0.06	-0.03	0.11**	0.27*	0.17	0.08
	(0.01)	(0.03)	(0.04)	(0.05)	(0.06)	(0.04)	(0.05)	(0.14)	(0.22)	(0.30)
$X_{i,t}$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
$X_{i,t}\Delta r_t$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cty FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
C-D F	-	-	-	-	-	14.72	14.72	14.72	14.72	14.72
min S-W F	-	-	-	-	-	23.36	23.36	23.36	23.36	23.36
R^2	0.68	0.58	0.49	0.46	0.45	0.68	0.52	0.33	0.36	0.33
N	932	932	932	932	932	932	932	932	932	932

Table reports estimations of IRFs of real output to a one percentage point interest rate change, and third order polynomial demographic controls. Clustered standard errors (country level) are in parenthesis with $\dagger p < 0.15, *p < 0.10, **p < 0.05, ***p < 0.01$ significance. Additional controls in $X_{i,t}$ are: log real consumption and log real investment per GDP. Regressions include two lags of the dependent variable as well as two lags and contemporaneous values of all additional controls. All controls are demeaned and we include interactions with interest rates (for KBO decomposition) and a dummy for 1973-1980 (to account for the well documented "price puzzle"). Cragg-Donald F-tests for weak instruments are reported as well as the minimum value among Sanderson-Windmeijer multivariate F-tests. Variables D2/D3 are scaled by 10/100 for readability.

We once again present the age-specific coefficients, now focusing on the $h = 2$ horizon, where the interaction terms in Table 2 are statistically significant. The patterns in Figure 5b closely resemble those in Figure 3b, so much of the earlier discussion continues to apply. As before, what matters most for these indirect, age-specific coefficients is their relative magnitude. When the baby boom cohort enters late career, the weight shifts from the relatively high early-career coefficients to the comparatively lower late-career ones, generating a negative contribution that amplifies the expected contractionary policy effect. However, because the estimated impact for retirees is particularly large, this effect is partially offset by gains in longevity, which increased the share of individuals over 70 prior to the baby

Figure 5: *Age Specific Estimates Output at H = 2: Composition + Indirect Age Coefficients*

(a) *Age Specific Coefficients: Composition Output Effect* **(b)** *Age Specific Coefficients: Indirect Output Effect (+$\sigma \Delta r_t$ Shock)*



boomers' entry into those age groups.

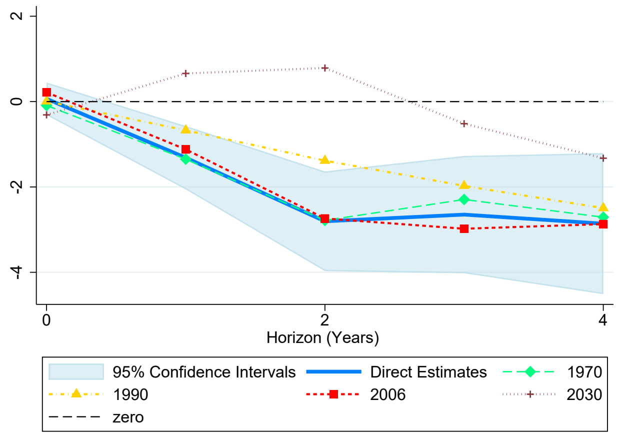
The combined implications of these dynamics—interacted with the same country-level age shares as above—are shown in Figure 6. The results indicate that population aging primarily delays the transmission of monetary policy to real output, with statistically significant and economically meaningful effects at horizons of one and two years. In the longer run, however, we find no persistent effect of policy on output. While the precise point estimates should be interpreted cautiously, the evidence in Figure 6 provides a coherent narrative: demographic composition shapes the timing rather than the magnitude of policy transmission to real activity. In section 4, we further examine whether these effects differ across the main components of GDP, i.e., consumption and investment, but ultimately find that the timing channel operates similarly through both.

4. Exploring Potential Mechanisms

The aggregate nature of the our data makes detailed understanding of mechanisms challenging. However, the JST data enables us to go at least one step further and investigate which sub-components of inflation and output might drive the results in section 3. We first evaluate whether the lack of responsiveness in output actually masks some important source of heterogeneity regarding other measures of economic activity, namely consump-

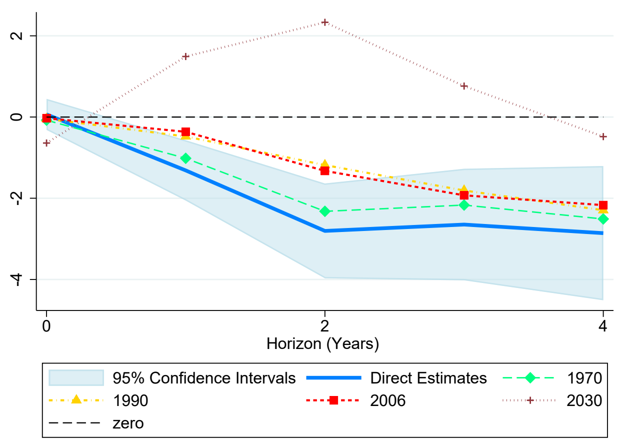
Figure 6: *Response of Output to Interest Rate Shock, KBO Decomposition: Full Age Controls*

(a) *Conditional IRF: United States*

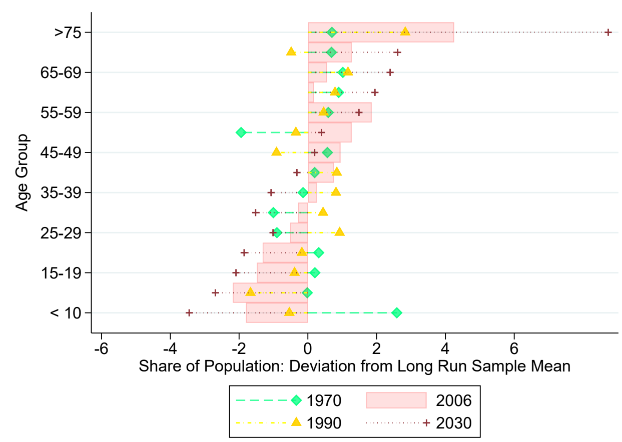


(b) *Population Shares: United States*

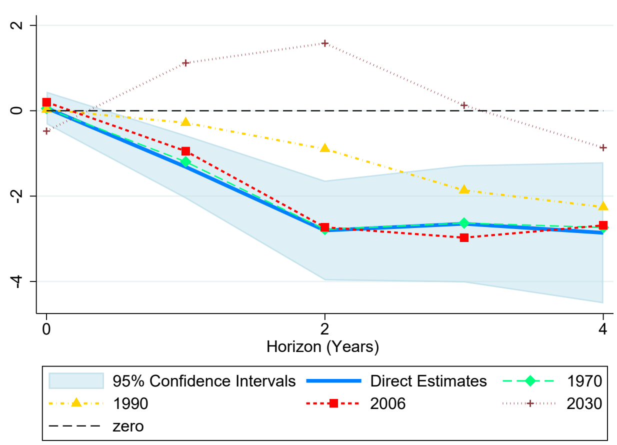
(c) *Conditional IRF: France*



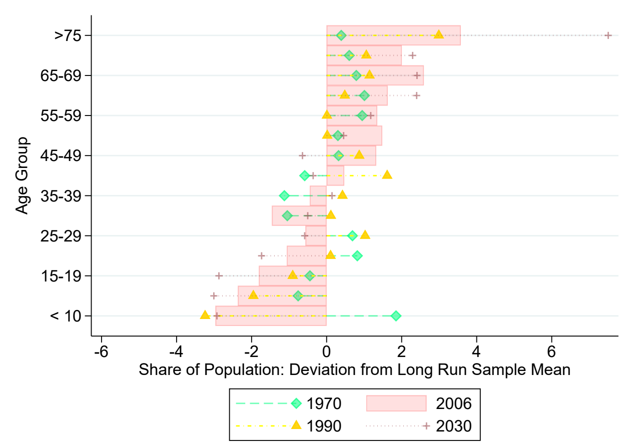
(d) *Population Shares: France*



(e) *Conditional IRF: Denmark*



(f) *Population Shares: Denmark*



Notes: Direct estimates are the average estimate of a one percentage point interest rate changes on output when population is at long run sample mean. Conditional IRFs are estimated effects of interest rate shocks conditional on age distribution of each country in a given year.

tion and investment. We then assess to what extent the effects on inflation are driven by changes in the labor market: exploring the response of wages and unemployment. Finally we consider the response of housing prices.

In section 3 we find a transitory impact of demographics on the transmission of policy to output, with the effect concentrated at the one and two-year horizon. To further unpack this we estimate the same IV specification on both consumption and investment. Kopecky (2023b) suggests that aging is important for both investment growth and capital deepening in the long run, in line with the original secular stagnation hypothesis of Hansen (1939). However, in this work, very different empirical relationships appear in the long run data for consumption and investment growth. Thus we wish to understand if there is heterogeneity in the transmission of monetary shocks to these component parts of output.

We report the relative estimated coefficients from the IV approach in Table 3. Ultimately we find little difference between the response of both consumption and investment and those we find for output above. For both, estimated effects of interaction terms with age structure are similarly contained in years one and two of the shock, before fading. The sign of these interaction terms are the same as those in Table 2. There is some suggestive evidence that may point to value in pursuing a more detailed understanding of household consumption and saving responses across the age distribution, but nothing that suggests that one of these channels is more compelling than the other.

Table 3: *Response of Consumption and Investment to Interest Rate Changes*

	Consumption Response: IV					Investment Response: IV				
Horizon, h	0	1	2	3	4	0	1	2	3	4
Δr_t	-0.16	-1.65***	-2.62***	-2.74***	-3.12***	1.14	-2.82**	-7.32***	-7.41**	-8.97**
	(0.24)	(0.51)	(0.79)	(0.95)	(1.14)	(0.98)	(1.13)	(2.50)	(3.05)	(3.83)
D1	0.10	0.82	1.00	0.63	1.09	-0.25	1.56	3.69	5.62	5.75
	(0.42)	(1.12)	(1.76)	(2.15)	(2.73)	(1.85)	(3.18)	(4.56)	(6.15)	(7.62)
D2	-0.48	-1.82	-2.67	-2.00	-2.94	1.30	-1.63	-5.81	-6.90	-4.54
	(0.80)	(1.82)	(3.18)	(3.78)	(4.60)	(3.63)	(5.65)	(7.88)	(9.91)	(12.20)
D3	0.27	0.87	1.40	1.03	1.45	-0.57	0.99	3.11	2.88	0.89
	(0.37)	(0.80)	(1.52)	(1.80)	(2.13)	(1.74)	(2.55)	(3.66)	(4.47)	(5.46)
$\Delta r_t \times D1$	0.03	0.22*	0.32**	0.19	0.14	-0.17	0.32	0.78**	0.61	0.53
	(0.07)	(0.13)	(0.15)	(0.20)	(0.25)	(0.18)	(0.24)	(0.39)	(0.52)	(0.79)
$\Delta r_t \times D2$	-0.09	-0.43*	-0.60**	-0.40	-0.27	0.26	-0.84*	-1.62**	-1.31	-1.24
	(0.13)	(0.24)	(0.29)	(0.39)	(0.50)	(0.34)	(0.44)	(0.70)	(1.03)	(1.62)
$\Delta r_t \times D3$	0.05	0.21*	0.29**	0.20	0.13	-0.12	0.46**	0.80**	0.65	0.65
	(0.06)	(0.12)	(0.14)	(0.19)	(0.25)	(0.18)	(0.22)	(0.34)	(0.51)	(0.81)
$X_{i,t}$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
$X_{i,t}\Delta r_t$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cty FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
C-D F	15.56	15.56	15.56	15.56	15.56	14.25	14.22	14.06	14	13.74
min S-W F	26.46	26.46	26.46	26.46	26.46	20.02	19.88	19.69	19.73	19.69
R^2	0.55	0.45	0.39	0.39	0.39	0.41	0.40	0.28	0.26	0.20
N	932	932	932	932	932	930	928	925	922	918

Table reports estimations of IRFs of real consumption and real investment per GDP to a one percentage point interest rate change, and third order polynomial demographic controls. Clustered standard errors (country level) are in parenthesis with $\dagger p < 0.15, *p < 0.10, **p < 0.05, ***p < 0.01$ significance. Additional controls in $X_{i,t}$ are: log real output and log cpi, and log real consumption/investment (when not the dependent variable). Regressions include two lags of the dependent variable as well as two lags and contemporaneous values of all additional controls. All controls are demeaned and we include interactions with interest rates (for KBO decomposition) and a dummy for 1973-1980 (to account for the well documented "price puzzle"). Cragg-Donald F-tests for weak instruments are reported as well as the minimum value among Sanderson-Windmeijer multivariate F-tests. Variables D2/D3 are scaled by 10/100 for readability.

We then shift our focus on the effects on the labor market which is considered to be particularly exposed to demographic trends. Indeed, changes in population distribution will likely impact both labor market participation and its composition. The size of the working-age population is expected to decrease in the coming decades due to the lower fertility rate and the exit of the relatively large baby boom cohort from the workforce. At the same, we are going to observe an increase in the relative share of older, and more productive, workers which will likely influence different dynamics in the labor market. More critically, labor market tightness is a critical variable for determining inflation risk.

We estimate the heterogeneous responses to monetary policy shocks using as dependent variable wages and unemployment rate. These results are reported in Table 4. Here, similar to CPI inflation, we find strong interactions between demographics and policy shocks on nominal wages at horizons 2-4. These are reported in Table 1. The direct impact we estimate here is quite large, about twice that of price inflation in Table 1. The interactions with demographics are similarly large, implying a substantial relationship between how this policy shock translates depending on the age structure of the population. The wage responsiveness is increasing with the share of young households and decreasing with the share middle-to-late career workers.

Table 4: *Response of Wages and Unemployment to Interest Rate Changes*

	Wage Response: IV					Unemployment Response: IV				
Horizon, h	0	1	2	3	4	0	1	2	3	4
Δr_t	-0.43	-2.16***	-4.19***	-5.93***	-7.12***	-0.14*	0.14†	0.55***	0.68**	0.72**
	(0.32)	(0.79)	(1.20)	(1.74)	(2.13)	(0.08)	(0.09)	(0.21)	(0.27)	(0.35)
D1	-0.89	-1.27	1.09	3.35	5.01	0.15	0.38	0.53	0.67	0.86
	(0.82)	(1.97)	(2.82)	(4.22)	(5.33)	(0.25)	(0.50)	(0.69)	(0.96)	(1.20)
D2	0.70	-0.43	-7.21†	-13.62**	-17.71**	-0.28	-0.66	-0.88	-0.83	-0.68
	(1.39)	(3.25)	(4.62)	(6.74)	(8.90)	(0.45)	(0.92)	(1.34)	(1.85)	(2.24)
D3	-0.12	0.82	4.57**	8.10***	10.09**	0.07	0.19	0.22	0.07	-0.16
	(0.63)	(1.46)	(2.13)	(3.12)	(4.23)	(0.21)	(0.45)	(0.67)	(0.94)	(1.14)
$\Delta r_t \times D1$	-0.03	0.27	0.75***	1.21***	1.55***	-0.02	-0.03	-0.03	0.00	0.06
	(0.11)	(0.22)	(0.29)	(0.40)	(0.52)	(0.03)	(0.03)	(0.03)	(0.06)	(0.09)
$\Delta r_t \times D2$	0.07	-0.46	-1.31**	-2.14***	-2.77***	0.02	0.04	0.05	0.02	-0.08
	(0.21)	(0.40)	(0.53)	(0.74)	(0.94)	(0.06)	(0.06)	(0.07)	(0.12)	(0.19)
$\Delta r_t \times D3$	-0.04	0.21	0.60**	0.98***	1.28***	-0.01	-0.02	-0.03	-0.02	0.03
	(0.10)	(0.19)	(0.25)	(0.35)	(0.44)	(0.03)	(0.03)	(0.04)	(0.06)	(0.09)
$X_{i,t}$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
$X_{i,t}\Delta r_t$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cty FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
C-D F	14.77	14.77	14.77	14.77	14.77	11.98	11.92	11.93	12	11.95
min S-W F	25.57	25.57	25.57	25.57	25.57	28.40	28.28	28.29	28.45	28.98
R^2	0.66	0.71	0.70	0.68	0.67	0.55	0.57	0.46	0.37	0.32
N	932	932	932	932	932	769	768	767	766	765

Table reports estimations of IRFs of log nominal wages and unemployment to a one percentage point interest rate change, and third order polynomial demographic controls. Clustered standard errors (country level) are in parenthesis with $\dagger p < 0.15, *p < 0.10, **p < 0.05, ***p < 0.01$ significance. Additional controls in $X_{i,t}$ are: log real output and log cpi, and log real consumption, and log investment/GDP. Regressions include two lags of the dependent variable as well as two lags and contemporaneous values of all additional controls. All controls are demeaned and we include interactions with interest rates (for KBO decomposition) and a dummy for 1973-1980 (to account for the well documented "price puzzle"). Cragg-Donald F-tests for weak instruments are reported as well as the minimum value among Sanderson-Windmeijer multivariate F-tests. Variables D2/D3 are scaled by 10/100 for readability.

Interestingly, while we find strong age-heterogeneity for wages, we find no demographic effects on unemployment. While policy has the expected direct effect, with a one-percentage point rate tightening increasing unemployment by 0.72 percentage points, but the demographic interactions are essentially zero. We note that unemployment data is missing for a larger portion of the sample so the sample size for these estimates is roughly 17% smaller than for our main results.

Ultimately, Table 4 suggests that labor market tightness induced by demographics affects the way that interest rate shocks translate into wages but not to unemployment. The sign in the three demographic-interest rate interaction terms with wage are the same as those for inflation in Table 1. This suggests that the relative effects across the age distribution will be quite similar to those in Figure 3. These are plotted relative to one another in Figure 7, along with house prices and the indirect effects are nearly identical, but are slightly less than twice as large. This scale is similar to the direct effects of the policy, which are -7.12 for nominal wage inflation and -3.82 for CPI inflation.

Having investigated CPI and nominal wage inflation responses we now turn to another important price and repeat our estimates for real house prices in Table 5. Our IV estimates suggest an even larger direct impact of interest rates, with a one percentage point increase in rates decreasing real house prices by 11.08 percent. Interactions with demographics suggest that population age structure strongly affect this transmission, with Figure 7 showing that these correspond to similar effects across the age distribution, and are quantitatively large.

Table 5: *Response of Housing Prices to Interest Rate Changes*

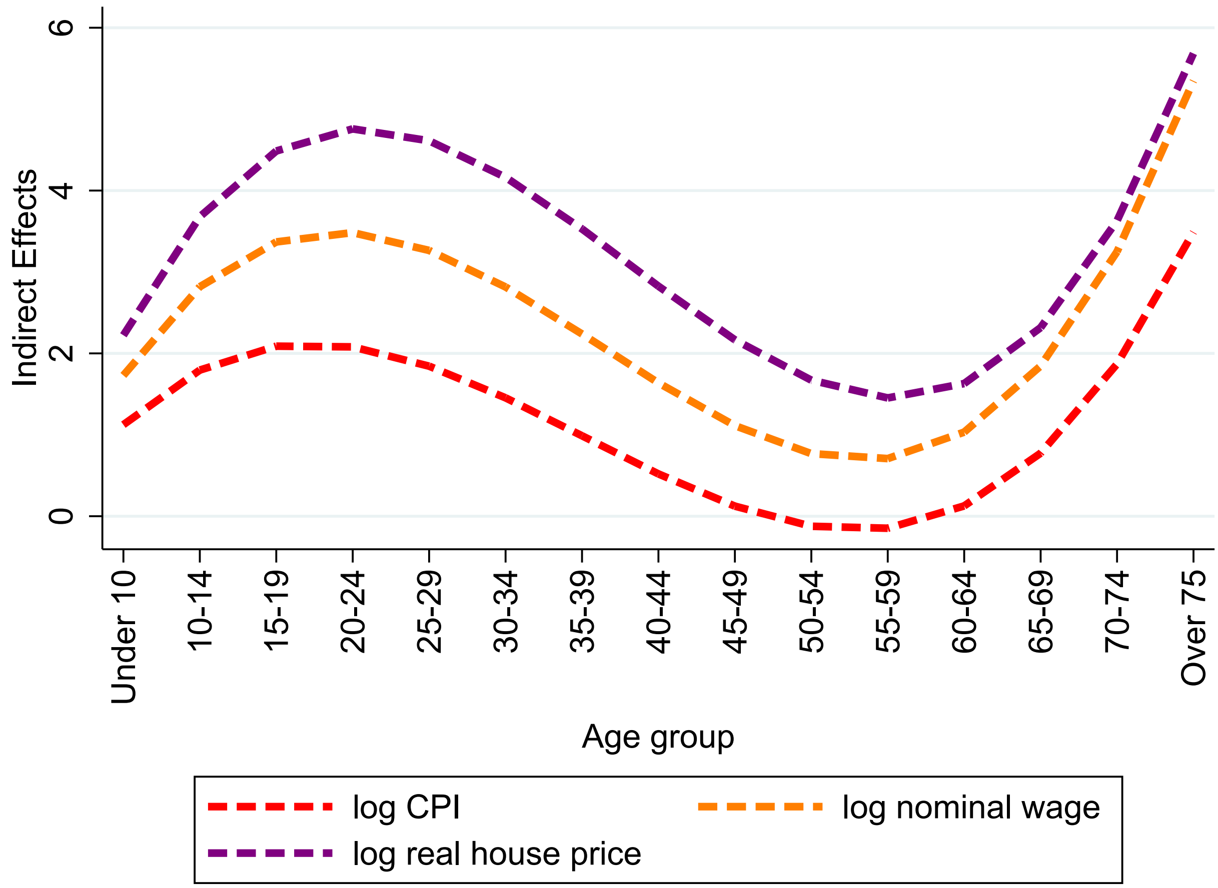
	House Price Response: OLS					House Price Response: IV				
Horizon, h	0	1	2	3	4	0	1	2	3	4
Δr_t	0.10	-1.20**	-2.38***	-2.92***	-2.91***	-0.40	-3.87***	-7.82***	-10.89***	-11.08***
	(0.35)	(0.45)	(0.56)	(0.61)	(0.64)	(0.70)	(1.27)	(2.12)	(3.63)	(3.68)
D1	-1.47	-0.02	1.64	5.03	6.70	-1.88	-2.00	-0.81	1.01	1.63
	(3.17)	(6.24)	(7.53)	(8.02)	(9.60)	(3.22)	(6.20)	(7.42)	(8.42)	(9.91)
D2	1.77	-0.21	-3.61	-8.57	-12.95	2.52	3.45	1.15	-0.85	-3.39
	(6.25)	(11.79)	(13.27)	(13.74)	(16.87)	(6.19)	(11.64)	(13.17)	(14.37)	(17.23)
D3	-0.71	-0.14	1.45	3.32	5.73	-1.06	-1.82	-0.76	-0.24	1.35
	(3.06)	(5.61)	(6.19)	(6.46)	(7.98)	(3.01)	(5.54)	(6.19)	(6.74)	(8.12)
$\Delta r_t \times D1$	-0.12	0.10	0.32*	0.46***	0.47**	-0.01	0.56*	1.57***	2.14**	1.97**
	(0.12)	(0.15)	(0.17)	(0.15)	(0.16)	(0.15)	(0.33)	(0.53)	(0.90)	(0.92)
$\Delta r_t \times D2$	0.35†	-0.04	-0.41	-0.67**	-0.67**	0.12	-0.79	-2.54**	-3.57**	-3.29*
	(0.22)	(0.26)	(0.32)	(0.29)	(0.32)	(0.30)	(0.64)	(1.00)	(1.72)	(1.83)
$\Delta r_t \times D3$	-0.19*	-0.01	0.15	0.27*	0.27†	-0.09	0.30	1.10**	1.57*	1.44†
	(0.10)	(0.13)	(0.16)	(0.15)	(0.16)	(0.15)	(0.31)	(0.48)	(0.83)	(0.90)
$X_{i,t}$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
$X_{i,t}\Delta r_t$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cty FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
C-D F	-	-	-	-	-	11.2	11.2	11.2	11.2	11.2
min S-W F	-	-	-	-	-	20.65	20.65	20.65	20.65	20.65
R^2	0.52	0.50	0.50	0.53	0.55	0.52	0.46	0.42	0.41	0.45
N	785	785	785	785	785	785	785	785	785	785

Table reports estimations of IRFs of for log real house prices to a one percentage point interest rate change, and third order polynomial demographic controls. Clustered standard errors (country level) are in parenthesis with $\dagger p < 0.15, *p < 0.10, **p < 0.05, ***p < 0.01$ significance. Additional controls in $X_{i,t}$ are: log real output and log cpi, and log real consumption, and log investment/GDP. Regressions include two lags of the dependent variable as well as two lags and contemporaneous values of all additional controls. All controls are demeaned and we include interactions with interest rates (for KBO decomposition) and a dummy for 1973-1980 (to account for the well documented "price puzzle"). Cragg-Donald F-tests for weak instruments are reported as well as the minimum value among Sanderson-Windmeijer multivariate F-tests. Variables D2/D3 are scaled by 10/100 for readability.

In Figure 7 we plot the indirect effects of the demographic interaction with interest shocks on wage and house prices. For reference we include the same indirect effect that is plotted in Figure 3b, showing that while there are some scale differences, that these reflect largely similar patterns in the relative impact across the age distribution. This can be further seen by the conditional impulse responses for wages and house prices in Figure 8. The average effects are larger for wages (and larger still for house prices) with the relative effect of demographics having similar impact to those seen in Figure 4 for CPI inflation.

While we find the particularly large direct effects on wage and house prices somewhat surprising, our main object of interest, the indirect effects, are of a similar scale across all three of these measures of price, with similar patterns emerging. Namely, that demographics appear to have roughly servied to accommodate the pass through of policy to these variables when there are large concentrations of youth in the 1970s, reduced the effect as the boomers

Figure 7: *Indirect Effects: CPI Inflation, nominal Wages, House Prices*



fully entered the workforce[11], temporarily reinforced the transmission again in 2006 as boomers enter late career, with the explosion of old age shares in the 2030 projection dominating and completely offsetting the direct policy impact.

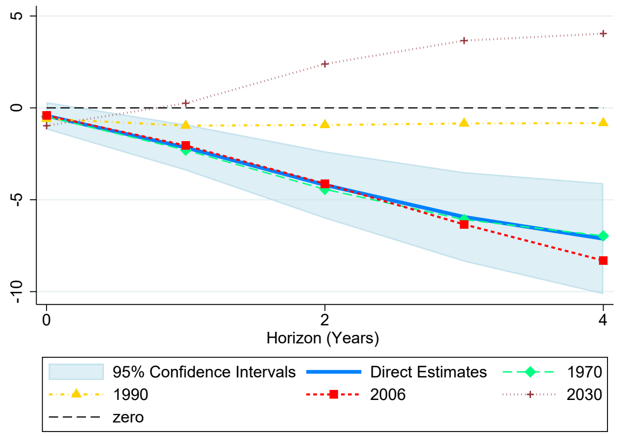
5. Conclusions

Monetary policy may see changes in its transmission as economies continue to age. However, the implications of these are likely quite different between the broad policy objectives of central banks: output, unemployment, and inflation. While output responses are affected in the short term when the underlying demographic structure moves, policy transmission to inflation appears to have long lasting effects. This is in line with recent evidence suggesting that population age will have implications for inflation pressure. Similar to the estimates of Leahy and Thapar (2019) on the impact of age structure on monetary transmission to

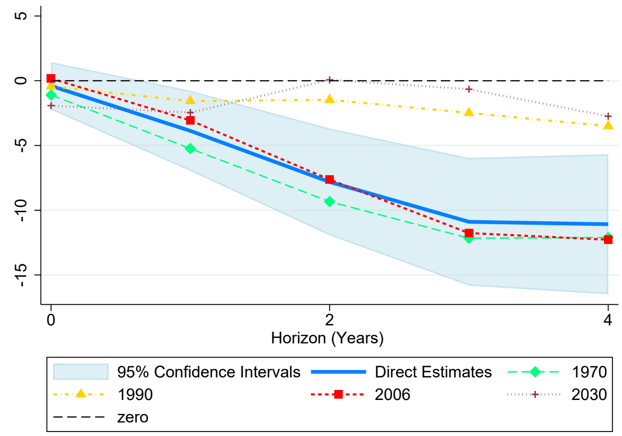
[11]The boomer cohort would be roughly mid 20s to mid 40s in 1990.

Figure 8: *Response of nominal Wage and real House Prices to Interest Rate Shock, KBO Decomposition: Full Age Controls*

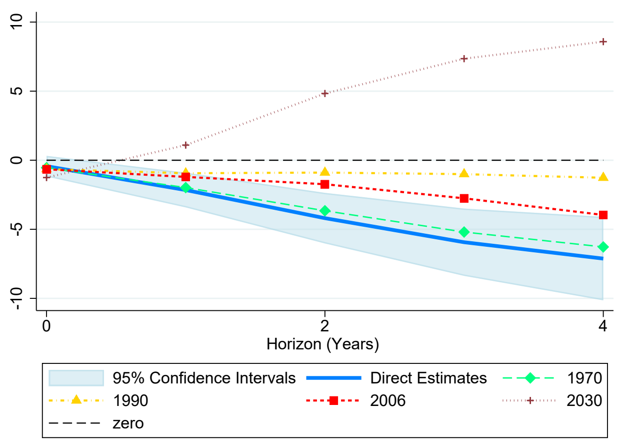
(a) *Conditional IRF, Wage: United States*



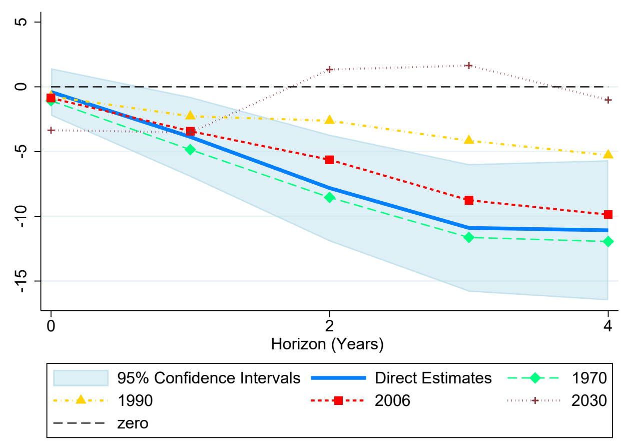
(b) *Conditional IRF, real HP: United States*



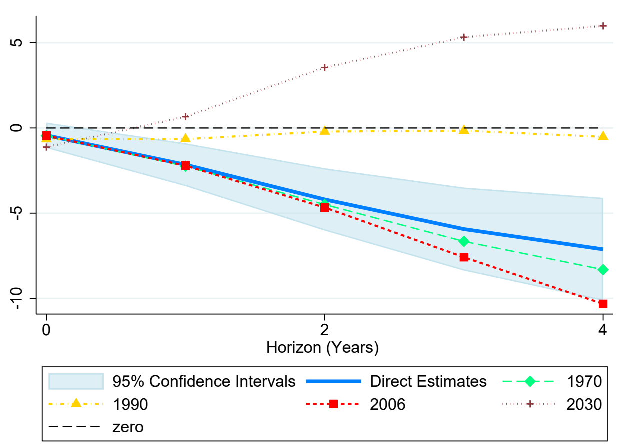
(c) *Conditional IRF, Wage: France*



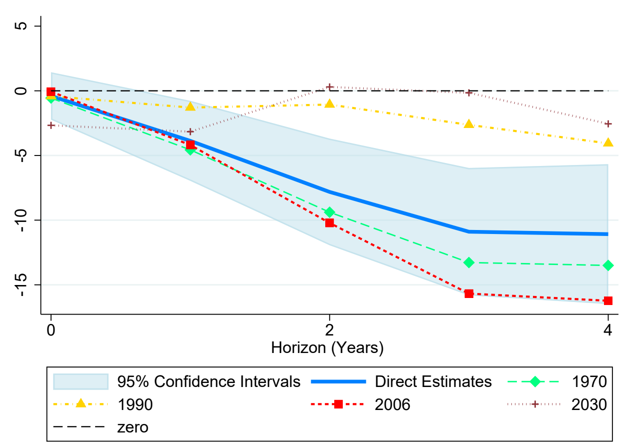
(d) *Conditional IRF, real HP: France*



(e) *Conditional IRF, Wage: Denmark*



(f) *Conditional IRF, real HP: Denmark*



Notes: Direct estimates are the average estimate of a one percentage point interest rate changes on wages and real house prices when population is at long run sample mean. Conditional IRFs are estimated effects of interest rate shocks conditional on age distribution of each country in a given year.

employment and income, we find that concentration of population in the earlier part of the life-cycle should put downward pressure on the impact of policy on inflation, while middle aged individuals should strongly reinforce transmission. Aging appears to delay policy impact on output, with no lasting effects, and has no impact on unemployment. We find particularly strong effect of retirees, perhaps due to their consumption of goods with highly rigid prices as shown in Mangiante (2024). Further work to explore these mechanisms, both empirically and with macroeconomic models will be crucial to fully understanding how trends in population age structure may alter the monetary toolbox in years to come.

In 2022 the oldest boomers were 76 and this outsized cohort has yet to exert the large negative pressure that we project by 2030. This is going to rapidly change in the coming years as the share of population over this age balloons. Demographics may still be accommodating interest rate policy to fight inflation, but if the estimates above are to be believed population age structure will begin to push hard against this quite rapidly in the coming years. Monetary authorities may soon see this traditional tool weaken just as inflation appears poised to return. If this is true then it will require more unconventional policy to exert control over these critical macroeconomic variables, with potentially more burden of responsibility placed on fiscal authorities to manage the macroeconomy responsibly.

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A. Further Discussion: Demographic Controls

Our estimates for effects across the entire age distribution build on the methodology of Fair and Dominguez (1991). Choosing demographic control variables is a somewhat difficult task. Many papers opt to use simple, relatively easy to understand statistics such as old-age dependence ratios, or working-age population shares. These are more intuitive and, if theoretically motivated, might be preferred because of the clarity they provide to exposition. However, using such estimates impose strict assumptions as to the specific age cutoffs where population weights matter. using dependence ratios requires that working-to-retiree (or young dependents) are the relevant groupings and do not allow that differences between young and old workers, young and old dependents, etc, can matter. One virtue of using Fair and Dominguez (1991) is that we don't ex ante impose which age groups matter. In subsection A.1 we provide more detail on the construction of these estimates. Then in subsection A.2 we provide some further discussion on the choice of order for the polynomial we use to fit the age distribution. We opt for a third degree polynomial, which we feel weights an inherent trade-off between wanting more flexibility[12] with concerns of over-fitting the data.

A.1. Construction of Demographic Controls

Suppose one wanted to estimate the following relationship:

$$y_{i,t} = X_{i,t}\beta + \sum_{j}^{J} \alpha_j p_{j,i,t} + \mu_i + \nu + \epsilon_{i,t}, \tag{7}$$

Where $y_{i,t}$ is any outcome of interest, $X_{i,t}$ is an arbitrary vector of controls, $\epsilon_{i,t}$ is error, μ_i country fixed effects, and ν a constant. The variables $p_{j,i,t}$ are shares of the population, divided into J bins. Because this is inestimable due to the perfect collinearity of the population shares $p_{j,i,t}$. Additionally while one would prefer to take a granular approach to modelling population shares allowing for a large number of, J, groups), these shares are highly collinear with one another, more so as their number increases. Finally, in smaller samples it may be undesirable to fit such a large number of coefficients, particularly as in our case when interaction terms would also be needed. By making the following two assumptions:

1. Letting α_j be the be the coefficient on population share $p_{j,i,t}$ of age group j in country i and time t. Assume that all of the effects of these coefficients across the age

[12] By flexibility we mean that we can allow for a larger number of turning points of the estimated effects across the age distribution, which we discuss below.

distribution sum to zero. In other words:

$$\sum_{j}^{J} \alpha_j = 0$$

2. Assume that the age coefficients α_j can be fitted with a K order polynomial. In other words:

$$\alpha_j = \sum_{k}^{K} \gamma_k j^k \tag{8}$$

All three problems are addressed. First it transforms the problem of estimating J coefficients into one of estimating K, as we will show in a moment. Second, the assumption that all age effects, α_j, sum to zero makes them jointly estimable. Third, by forcing the age effects to lie on a polynomial, the model requires that there be relatively smooth transitions from the effect of one age group to another. If one were to take only the first assumption (or omit the constant of the regression) it would be possible to estimate the effects in Equation 7. The results of such estimations when using five or ten year population age groups often lead to highly unstable coefficients that alternate signs quickly from one age group to the next. This is due to the high degree of collinearity between one age group and those immediately around it, which increases in J.

To see how this methodology works. Substitute $alpha_j$ into Equation 7. We will assume in what follows a third order polynomial for exposition. This yields:

$$y_{i,t} = X_{i,t}\beta + \sum_{j}^{J} \left[(\gamma_0 + \gamma_1 j + \gamma_2 j^2 + \gamma_3 j^3) p_{j,i,t} \right] + \mu_i + \nu + \epsilon_{i,t} \tag{9}$$

The summing over both sides of the second equation and using the assumption that the sum of α_j must be zero, it can easily be shown that γ_0 is equal to:

$$\gamma_0 = -\frac{1}{J} \left[\gamma_1 \sum_j j + \gamma_2 \sum_j j^2 + \gamma_3 \sum_j j^3 \right]$$

Thus far we have followed exactly the methodology of Fair and Dominguez (1991). From here one simply plugs the above expression for γ_0 into Equation 9, and given the fact that the first term, $sum_j \gamma_0 p_{j,i,t} = \gamma_0$ by the fact that the population parameters sum to one then one can rearrange this equation as:

$$y_{i,t} = X_{i,t}\beta + \gamma_1 \sum_j^J \left(p_{j,i,t} j - \frac{\sum j}{J} \right) + \gamma_2 \sum_j^J \left(p_{j,i,t} j^2 - \frac{\sum j^2}{J} \right) + \gamma_3 \sum_j^J \left(p_{j,i,t} j^3 - \frac{\sum j^3}{J} \right) + \mu_i + \nu + \epsilon_{i,t}. \tag{10}$$

With the terms in parenthesis being the demographic variables. Because we wanted our estimates to follow the demeaned structure and interpretability of for the Blinder-Oaxaca decomposition. We opted to instead estimate:

$$y_{i,t} = X_{i,t}\beta + \sum_j^J \alpha_j (p_{j,i,t} - \bar{p}_{j,t}) + \mu_i + \nu + \epsilon_{i,t}. \tag{11}$$

The first few steps are exactly the same so we don't replicate them here. The problem however is just to rearrange terms slightly differently in order to construct the correct demographic variables for estimation. In principle this simplifies to:

$$Dk_{i,t} = \left[\sum_j^J (p_{j,i,t} - \bar{p}_{i,t}) j^k - \sum_j^J j^k \sum_j^J (p_{j,i,t} - \bar{p}_{i,t}) \right]. \tag{12}$$

But only this first term is needed given that $sum_j \gamma_0 (p_{j,i,t} - \bar{p}_{j,t}) = 0$, and not γ_0 as before. So rather the estimation becomes:

$$y_{i,t} = X_{i,t}\beta + \gamma_1 \sum_j^J (p_{j,i,t} - \bar{p}_{j,t}) j + \gamma_2 \sum_j^J (p_{j,i,t} - \bar{p}_{j,t}) j^2 + \gamma_3 \sum_j^J (p_{j,i,t} - \bar{p}_{j,t}) j^3 + \mu_i + \nu + \epsilon_{i,t}, \tag{13}$$

Where these $\sum_j (p_{j,i,t} - \bar{p}_{j,t}) j^k$ terms are the demographic controls used in the estimations in the paper.

A.2. Using Higher Oder Polynomials for Fair and Dominguez (1991)

In our preferred specification we use third order polynomial. Setting the polynomial to K implies a maximum $K - 1$ turning points. A well known critique of the Fair and Dominguez (1991) approach is concern that this polynomial will over-fit the data, particularly with extreme values at the tails of the age distribution. This is balanced against a desire to allow for appropriate curvature to capture the empirical relationship in the data. While to our knowledge there is no specific test for an optimal way to balance these concerns we demonstrate in this section our thinking regarding weighing three potential tradeoffs by answering the following questions:

1. Do we capture the necessary variation in effect by age?
2. Do we minimize concerns with overfitting, particularly for age groups at the top and bottom of the distribution?
3. Is our preferred specification (IV) still valid?

Ultimately while we think there could be some variation in age groups that we miss with our third order polynomial,[13], we deem the risks of overfitting, and loss of instrument power to be too great to merit using 4th or higher polynomials instead. We do however show that the quantitative implications of our results for fourth and fifth order polynomials are broadly in line with those discussed in the paper with the most noticeable differences coming through extreme weights on old age shares that become particularly important in more recent years and future projections.

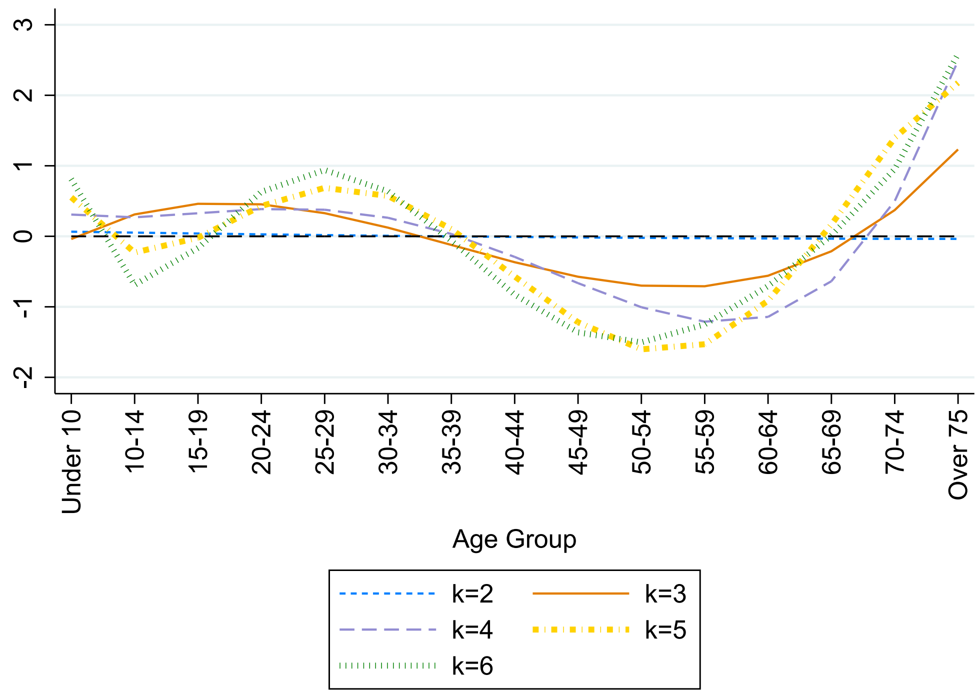
To first demonstrate the role that increase polynomial order, K, has on the shape of the indirect effect (marginal age effect of the interaction term) we show the age-specific coefficients for the indirect effect on inflation, using the same standard deviation interest rate shock as in the paper for the baseline IV model for all $K \in \{1, 2, 3, 4, 5, 6\}$. These can be seen in Figure 9. We note that these effects have been demeaned for ease of comparison. This doesn't affect interpretation as the indirect-age effects need not sum to zero, but because population age shares (which are demeaned as all controls) do sum to zero, it is only the relative size of marginal age-effects that matter.

As we increase the order of the polynomial there does appear to be some convergence towards a consistent shape that is broadly in line with our estimates using the third order polynomial, with the more critical turning points (at the 35-39, and 65-69 groups) appearing broadly consistent. However, it does appear in Figure 9 that we potentially miss variation relating to young workers and dependents, which at higher orders seem to suggest that young dependents may have a lower effect that is missed in our current estimation. These might suggest that using a 5th or 6th order polynomial could provide further insight relative to our estimate. However for all specifications over $K = 3$, we see extreme values for the over 75 group, whose coefficient was already fairly large in our baseline estimates. Ultimately when weighing these two our impression is that the added insight provided by higher dimensions is offset by concerns related to doubling the already outsized influence of this group.

To further understand if this choice has implications on our estimates we now report the regression and conditional impulse response functions for our baseline inflation estimate using $K = 4$ and $K = 5$ specifications of our Fair and Dominguez (1991) demographic

[13] That is there is a degree to which question one is not fully a "yes".

Figure 9: *Age Specific Coefficients: Indirect Inflation Effect ($+\sigma\Delta r_t$ Shock): Varying K*



variables. These are reported in Table 6. Two issues arise that speak to whether we wish to use these. The first is that as demographic terms are added the individual significance of each coefficient of interaction falls. These are still fairly strongly significant in the case of the fourth order polynomial, but only marginal in the fifth. In both cases this is not terribly troubling as really what might matter more should be the joint significance of the entire set of coefficients, which is still significant in both cases.[14] What is more troubling is that the Cragg-Donald F-test for these specifications is now below the heuristic 10 that many use as a cutoff for sufficient power in an IV regression. We note that the overall test of excluded instruments is always (both here and in our baseline estimates) much larger than this value, with the lowest value from each Sanderson-Windmeijer multivariate first stage F of excluded instruments above this threshold for the fifth order polynomial. However, we prefer to use a more conservative estimation as our main result given the potential for weak instruments here, particularly when taken together with concerns of over-fitting above.

[14]For the fourth order the null that all are zero is rejected with a p-value less than 0.01 level and for fifth less than 0.05.

Table 6: *Robustness: Higher Order Polynomials*

	Δ Log CPI: $K = 4$					Δ log CPI: $K = 5$				
Horizon, h	0	1	2	3	4	0	1	2	3	4
Δr_t	-0.30	-0.75	-1.37*	-2.74**	-3.89**	-0.40	-1.12	-1.74*	-3.11**	-4.47**
	(0.35)	(0.60)	(0.70)	(1.11)	(1.64)	(0.42)	(0.87)	(1.00)	(1.50)	(2.19)
D1	-5.81***	-12.33***	-17.81***	-23.23***	-30.64***	-1.43	-2.58	1.57	11.37	17.25
	(1.67)	(3.00)	(4.17)	(5.39)	(7.75)	(3.89)	(9.77)	(16.04)	(20.46)	(25.69)
D2	17.75***	38.76***	57.06***	77.28***	101.86***	-1.77	-4.02	-27.37	-66.35	-91.69
	(5.33)	(9.79)	(14.10)	(18.36)	(25.26)	(16.95)	(42.77)	(69.63)	(90.01)	(112.65)
D3	-18.22***	-40.79***	-61.28***	-84.66***	-111.23***	14.83	30.47	79.00	143.40	186.72
	(5.41)	(10.45)	(15.68)	(20.63)	(27.67)	(28.49)	(71.27)	(114.05)	(148.76)	(187.57)
D4	5.85***	13.40***	20.44***	28.53***	37.25***	-17.50	-36.15	-77.06	-123.03	-154.02
	(1.76)	(3.56)	(5.48)	(7.29)	(9.57)	(20.13)	(49.67)	(78.11)	(102.72)	(131.05)
D5						5.82	12.17	23.93	35.56	43.20
						(5.01)	(12.21)	(18.92)	(25.08)	(32.44)
$\Delta r_t \times D1$	-0.31*	-0.34	-0.40	-0.56	-0.78	-0.92	-2.37	-2.70	-3.64	-6.12†
	(0.18)	(0.34)	(0.55)	(0.75)	(0.91)	(0.70)	(1.99)	(2.17)	(2.72)	(3.99)
$\Delta r_t \times D2$	0.97**	1.21	1.52	2.34	3.28	3.42	9.38	10.84	14.86	25.05†
	(0.44)	(0.84)	(1.36)	(1.91)	(2.33)	(2.74)	(7.81)	(8.38)	(10.60)	(15.69)
$\Delta r_t \times D3$	-1.16**	-1.62*	-2.16†	-3.43*	-4.79*	-5.22	-15.16	-17.62	-24.33	-41.09†
	(0.45)	(0.84)	(1.35)	(1.95)	(2.47)	(4.42)	(12.64)	(13.44)	(17.11)	(25.39)
$\Delta r_t \times D4$	0.44***	0.66**	0.91*	1.46**	2.03**	3.36	10.36	12.02	16.55	28.24†
	(0.16)	(0.30)	(0.46)	(0.68)	(0.90)	(3.07)	(8.82)	(9.32)	(11.88)	(17.64)
$\Delta r_t \times D5$						-0.75	-2.49	-2.87	-3.91	-6.79†
						(0.76)	(2.20)	(2.31)	(2.94)	(4.36)
$X_{i,t}$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
$X_{i,t}\Delta r_t$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cty FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
C-D F	7.34	7.34	7.34	7.34	7.34	4.61	4.61	4.61	4.61	4.61
min S-W F	23.60	23.60	23.60	23.60	23.60	14.29	14.28	14.30	14.30	14.30
R2	0.63	0.65	0.65	0.62	0.56	0.63	0.63	0.64	0.61	0.56
N	932	932	932	932	932	932	932	932	932	932

Table reports estimations of IRFs of CPI Inflation to a one percentage point interest rate change, and fourth and fifth order polynomial demographic controls. Clustered standard errors (country level) are in parenthesis with $\dagger p < 0.15, *p < 0.10, **p < 0.05, ***p < 0.01$ significance. Additional controls in $X_{i,t}$ are: log real consumption and log real investment per GDP. Regressions include two lags of the dependent variable as well as two lags and contemporaneous values of all additional controls. All controls are demeaned and interacted with interest rates as well as a dummy for 1973-1980 to account for the well documented "price puzzle." Cragg-Donald F-tests for weak instruments are reported as well as the minimum value among Sanderson-Windmeijer multivariate F-tests. Variables D2/D3 are scaled by 10/100 for readability.

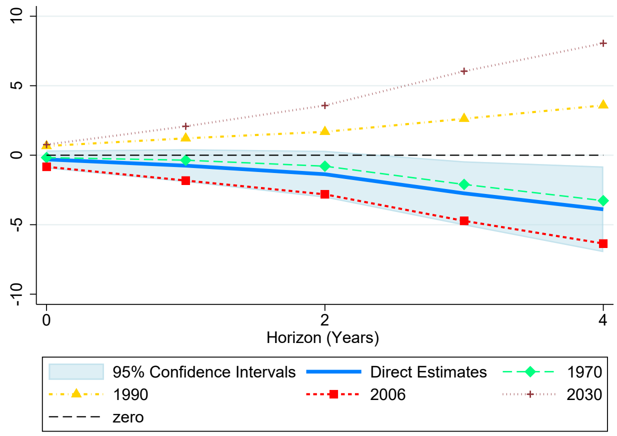
To see whether this choice substantially affects the overall story of our paper we recreate the impulse response functions of Figure 4 using these estimations. We do not repeat the age graphs to economize on space but the same years (both in and out of sample) are used to generate these conditional IRFs. The primary difference between these results and our baseline estimates are that older age shares exert higher influence. Projected 2030 values for France, the oldest country we report here have gone from implausibly large to outside the realm of possibility. However the general pattern in terms of how age structure makes policy qualitatively more or less powerful generally holds true to all discussions above. Since we don't wish to stake too bold a claim on these point estimates we are comforted by the fact that the qualitative nature of results appear to be robust to choices over how to model this particular parameter as we view the relative implications in a broad sense to be similar no matter how one chooses to set demographics in this Fair and Dominguez (1991) framework.

B. Robustness: Full Sample Estimation

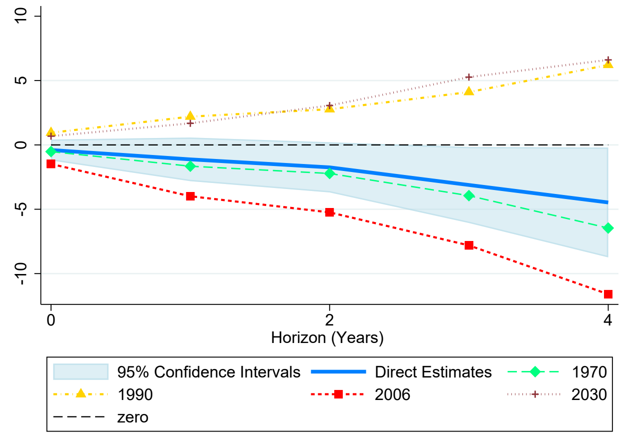
We estimate our sample on the pre-2006 period to avoid any potential short-term complications arising from both the Global Financial Crisis and in the final periods, the Covid-19 epidemic. We also felt this added some more direct comparability of our estimates to those from Jordà et al. (2020) whose identification strategy we adopt. However, we wish to emphasize that this is not an assumption that alters our estimates in a particularly meaningful way. In this section we provide reestimations of our baseline results when extending the sample to the 2020 end of R6 version of the Jordà et al. (2017) macro history dataset that we use. At current writing this remains the most up-to-date version of this data. Both the direct effects and interaction terms of interest have the same signs and significance as in the paper and a somewhat similar magnitude. Further, the instrument becomes stronger with this longer panel. The medium term indirect effects of aging on output are also in this longer panel slightly more significant, which perhaps lends slightly more credibility to those reported in Table 2. Given that the magnitudes are nearly identical for this two-year horizon all of the conditional IRFs at this two year horizon will be as in the main body, but we prefer to report the more conservative standard errors there.

Figure 10: *Inflation Response to Interest Rate Shock, KBO Decomposition: Varying K*

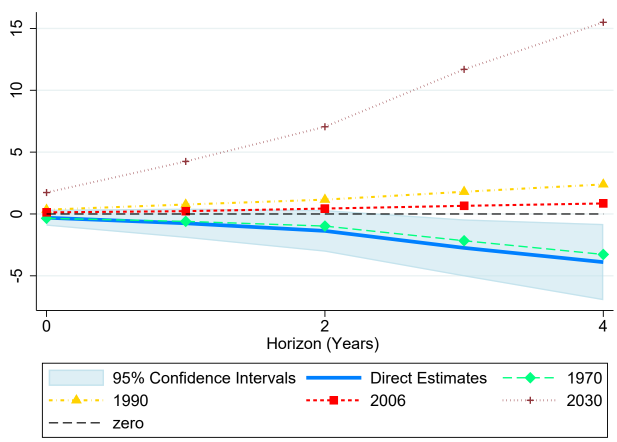
(a) *Conditional IRF* $k = 4$*: United States*



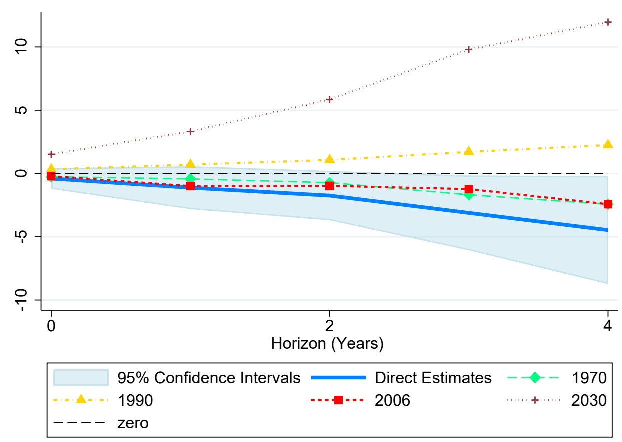
(b) *Conditional IRF* $k = 5$*: United States*



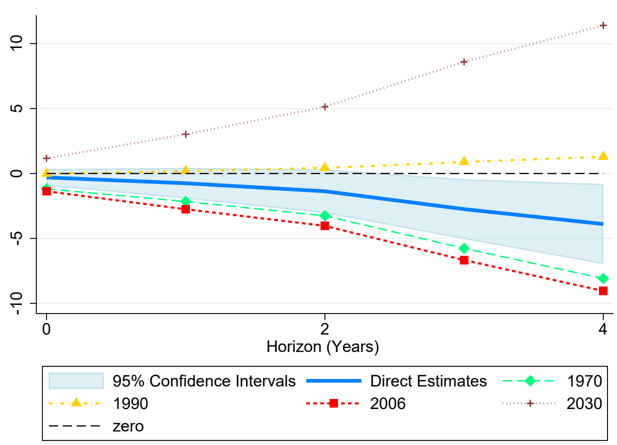
(c) *Conditional IRF* $k = 4$*: France*



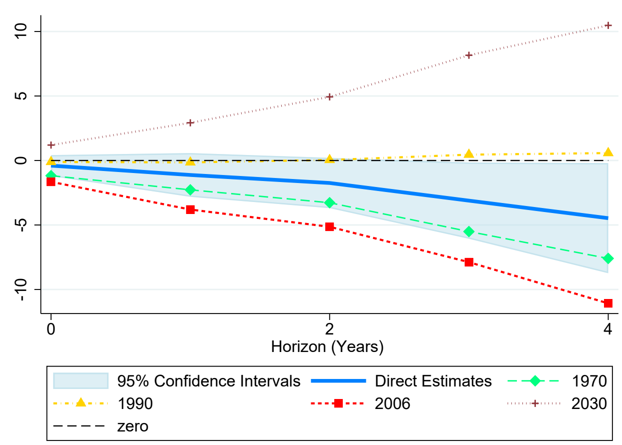
(d) *Conditional IRF* $k = 5$*: France*



(e) *Conditional IRF* $k = 4$*: Denmark*



(f) *Conditional IRF* $k = 5$*: Denmark*



Notes: Direct estimates are the average estimate of a one percentage point interest rate changes on inflation when population is at long run sample mean. Conditional IRFs are estimated effects of interest rate shocks conditional on age distribution of each country in a given year.

Table 7: *Robustness: Extending Our Sample*

	Δ Log Output					Δ log CPI				
Horizon, h	0	1	2	3	4	0	1	2	3	4
Δr_t	0.06	-1.47***	-3.06***	-2.91***	-3.23**	-0.14	-0.61	-1.32**	-2.46***	-3.31***
	(0.18)	(0.44)	(0.91)	(1.12)	(1.28)	(0.26)	(0.46)	(0.57)	(0.90)	(1.26)
D1	0.02	1.16	1.78	1.80	2.16	-0.16	0.50	2.48**	5.51***	8.38***
	(0.25)	(0.92)	(1.54)	(1.82)	(2.37)	(0.45)	(0.83)	(1.25)	(1.87)	(2.80)
D2	0.48	-1.55	-2.86	-2.96	-3.44	-0.39	-2.63	-7.42***	-13.47***	-19.40***
	(0.51)	(1.61)	(2.75)	(3.02)	(3.63)	(1.06)	(1.92)	(2.81)	(4.11)	(5.90)
D3	-0.36	0.50	1.16	1.14	1.24	0.28	1.50	3.81**	6.53***	9.16***
	(0.26)	(0.73)	(1.25)	(1.38)	(1.59)	(0.57)	(1.08)	(1.57)	(2.26)	(3.12)
$\Delta r_t \times D1$	-0.03	0.13**	0.31**	0.15	0.08	0.04	0.17	0.31†	0.58**	0.81**
	(0.04)	(0.06)	(0.15)	(0.20)	(0.24)	(0.08)	(0.15)	(0.19)	(0.28)	(0.37)
$\Delta r_t \times D2$	0.07	-0.23**	-0.55*	-0.32	-0.18	-0.11	-0.36	-0.63*	-1.14**	-1.57**
	(0.08)	(0.12)	(0.29)	(0.40)	(0.49)	(0.14)	(0.26)	(0.34)	(0.47)	(0.62)
$\Delta r_t \times D3$	-0.03	0.11*	0.26*	0.17	0.10	0.06	0.18	0.30*	0.55**	0.75***
	(0.04)	(0.06)	(0.15)	(0.20)	(0.24)	(0.07)	(0.12)	(0.16)	(0.22)	(0.28)
$X_{i,t}$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
$X_{i,t}\Delta r_t$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cty FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
C-D F	20.87	20.87	20.87	20.87	20.67	19.97	19.97	19.97	19.97	19.89
min S-W F	21.11	21.11	21.11	21.11	20.98	21.44	21.44	21.44	21.44	21.49
R2	0.70	0.55	0.36	0.40	0.37	0.70	0.71	0.72	0.70	0.66
N	1022	1022	1022	1022	1017	1022	1022	1022	1022	1018

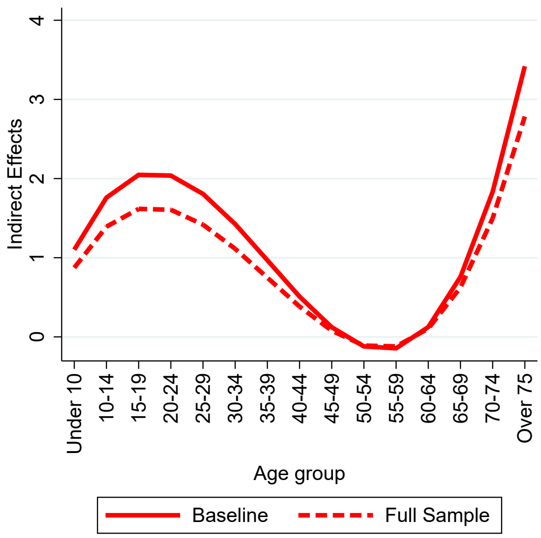
Table reports estimations of IRFs of log CPI inflation and log real GDP to a one percentage point interest rate change, and third order polynomial demographic controls. Clustered standard errors (country level) are in parenthesis with $\dagger p < 0.15, *p < 0.10, **p < 0.05, ***p < 0.01$ significance. Additional controls in $X_{i,t}$ are: log real consumption and log real investment per GDP. Regressions include two lags of the dependent variable as well as two lags and contemporaneous values of all additional controls. All controls are demeaned and interacted with interest rates as well as a dummy for 1973-1980 to account for the well documented "price puzzle." Cragg-Donald F-tests for weak instruments are reported as well as the minimum value among Sanderson-Windmeijer multivariate F-tests. Variables D2/D3 are scaled by 10/100 for readability.

To understand in general whether this sample selection affects the age specific coefficients on these indirect effects we plot those from the sample used in the paper, and the unrestricted (full sample) used above for all of the outcomes we study except for unemployment (which remains insignificant at all horizons). These are reported in Figure 11. For each outcome we report the full horizon if interactions are significant at that time, and otherwise report the two-year horizon for which output, investment, and consumption are significant. Recall that while these interaction coefficients for marginal indirect age effects need not sum to zero (and are interacted here with a standard deviation shock to the monetary policy rate) that the demeaned population age shares do sum to zero. Thus when weight is added to one group weight is symmetrically taken away elsewhere, so it is the relative size of these coefficients that matter.

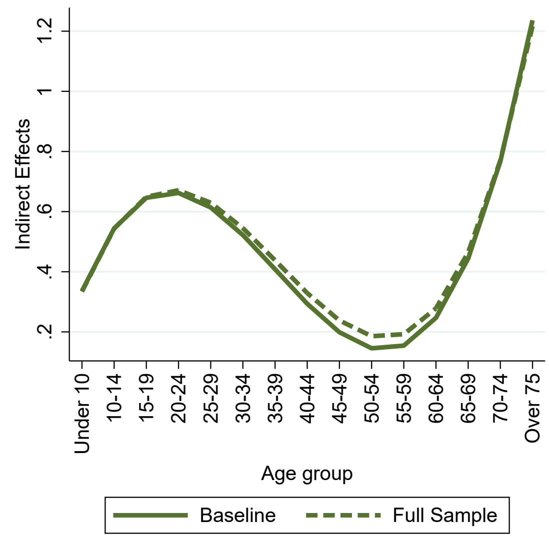
For this robustness what matters is whether these indirect effects are dramatically different than those for our baseline estimates. Figure 11 plots both those implied by the preferred specification in the paper against those implied by a full sample estimation as above (for space we do not report tables for all). The outcome where there may be some meaningful made from shortening our sample are the results with real housing prices as an outcome, as seen in Figure 11f. Indeed this is the only specification that goes from strongly significant at the full horizon to being insignificant. Given that housing markets were at the center of the global crisis it is perhaps expected that this would be the outcome most affected, and we largely view this as perhaps a great deal of movement induced by other factors making a demographic effect harder to detect. While the broad quantitative story would be similar using these coefficients, they reflect a less intense impact of age on monetary transmission. However, the volatility induced by changing samples cautions against taking those particular estimates as being very precisely estimated.

Figure 11: *Indirect Effects Age Effects: Baseline and Full-Sample Comparison*

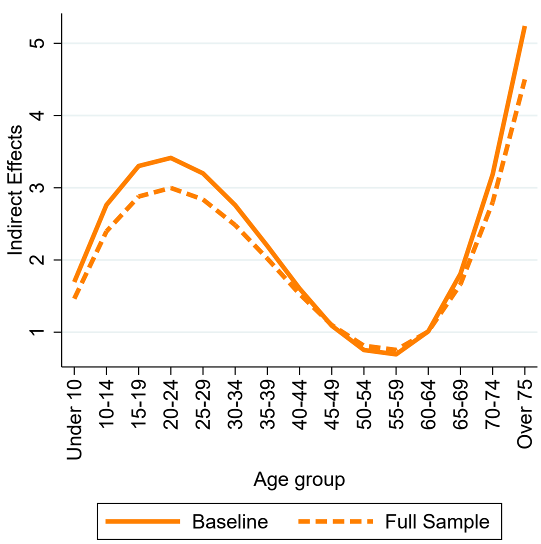
(a) *Log CPI*, $h = 4$



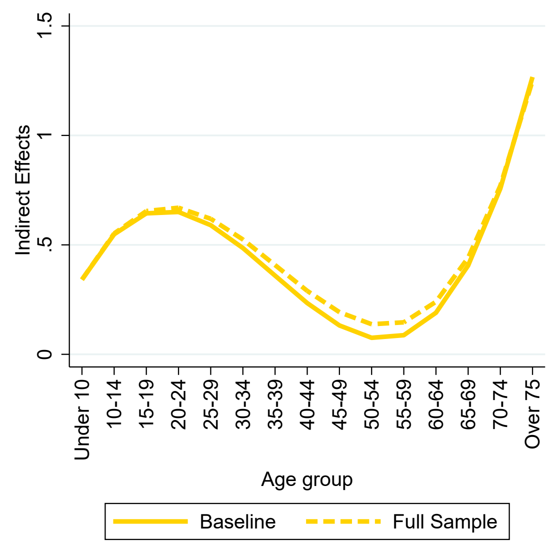
(b) *Log Output*, $h = 2$



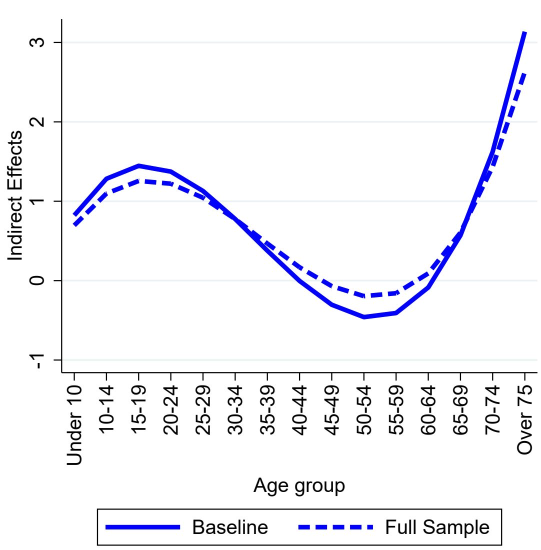
(c) *Log Wage*, $h = 4$



(d) *Log real consumption*, $h = 2$



(e) *Log real investment*, $h = 4$



(f) *Log real house prices*, $h = 4$