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Inflation Inequality: Measurement, Causes, and Policy Implications

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Abstract

Does inflation vary across the income distribution? This article reviews the growing literature on inflation inequality, describing recent advances and opportunities for further research in four areas. First, new price index theory facilitates the study of inflation inequality. Second, new data show that inflation rates decline with household income in the United States. Accurate measurement requires granular price and expenditure data because of aggregation bias. Third, new evidence quantifies the impacts of innovation and trade on inflation inequality. Contrary to common wisdom, empirical estimates show that the direction of innovation is a significant driver of inflation inequality in the United States, whereas trade has similar price effects across the income distribution. Fourth, inflation inequality and non-homotheticities have important policy implications. They transform cost-benefit analysis, optimal taxation, the effectiveness of stabilization policies, and our understanding of secular macroeconomic trends—including structural change, the decline in the labor share and interest rates, and labor market polarization.

1. INTRODUCTION

Should we take seriously the idea that inflation varies across the income distribution? It has been known since at least Engel's (1857) work that households with different incomes consume different goods and services; these differences in consumption bundles create the potential for inflation inequality. However, little is known regarding whether inflation rates differ across income groups in practice. Is inflation inequality large? If so, why does it arise, and what are the policy implications? In the last few years, research in economics has made substantial progress on these questions thanks to new data, which are granular enough to detect inflation inequality, and to new theoretical frameworks, which help guide empirical analysis and draw policy implications. This article surveys these recent advances and highlights opportunities for further research.

First, recent developments in price index theory facilitate the study of heterogeneity in inflation across household groups. Group-specific price indices are robust to several sources of bias in the measurement of inflation—including expenditure switching, changes in product variety, and taste shocks. The recent development of tractable non-homothetic price indices makes it possible to carry out a continuous analysis of price indices across the household income distribution.

Second, granular data reveal that inflation inequality can be large. In the United States, recent work documents that inflation rates decline with income. These findings overturn results from prior work, which used coarser product categories and concluded that inflation inequality was small. Inflation inequality is only visible with more granular data—for example, when using the most detailed product categories available from standard consumption and price surveys compiled by statistical agencies, or with scanner data. Because of aggregation bias, it is crucial to eventually obtain micro data for each sector of the economy to accurately measure effective prices paid, expenditure shares, and product variety across sociodemographic groups.

Third, empirically the direction of innovation turns out to be a significant driver of inflation inequality. Contrary to common wisdom, innovation does not always benefit all consumers through trickle-down mechanisms and the product cycle, simply because product markets are segmented. In the presence of increasing returns to scale, growing markets experience productivity gains and lower inflation. Because of economic growth and rising nominal income inequality, the market size for high-end (income-elastic) products increases faster, which creates incentives for entry in product categories catering to the rich. Recent work estimates the causal relationship between market size and consumer prices, and it finds that changes in nominal inequality are magnified by the endogenous response of innovation.

Fourth, international trade does not seem to lead to a systematic divergence in price indices across the income distribution. Several important channels must be taken into account to measure the distributional effects of trade via prices, including heterogeneity in import shares, expenditure switching, and pass-through heterogeneity. In some contexts, the implications of trade for inflation inequality can be large. However, for the United States most of the evidence suggests that increased trade did not lead to a divergence in inflation rates across income groups over the past 20 years. This finding contradicts the view, still widely held, that trade primarily reduces prices for the poor in the United States.

Fifth, inflation inequality has many policy implications. It affects the cost-benefit analysis as well as the optimal design of policies. Several recent papers show how to incorporate price index heterogeneity into the study of optimal commodity and income taxation. Quantitative estimates indicate substantial welfare losses from ignoring non-homotheticities and the equilibrium response of prices in optimal policy design. Recent work also shows that heterogeneity in consumption baskets matters for stabilization policy, notably monetary policy. Richer households, that have lower marginal propensities to consume, spend more on sectors with higher price rigidities. Because of this fact, the effectiveness of monetary policy is reduced in general equilibrium.

Finally, a growing literature shows that non-homotheticities help understand long-term macroeconomic trends—including structural change, the decline in the labor share and real interest rates, the rise in wealth-to-income ratios, labor market polarization, and the severity of recessions. These analyses shed new light on the underlying causes of these trends and the appropriate policy responses.

This article is organized as follows. Section 2 is a primer on price indices with household heterogeneity. Section 3 describes the recent evidence on the measurement of inflation inequality. Section 4 analyzes the potential causes of inflation inequality, focusing on innovation and trade. Section 5 discusses the relevance of these findings for policy.

2. A PRIMER ON PRICE INDICES AND HOUSEHOLD HETEROGENEITY

This section discusses how price indices can account for household heterogeneity, using either group-specific homothetic price indices or non-homothetic price indices.

2.1. Heterogeneous Homothetic Price Indices

Price indices aim at measuring how the cost of reaching a certain level of utility U changes over time. The change in the cost of achieving U from t to $t+1$ is given by the ratio of expenditure functions, i.e.,

$$1 + \pi_{t,t+1,U} \equiv \frac{e(U, \mathbf{p}_{t+1})}{e(U, \mathbf{p}_t)},$$

where the price vectors $\mathbf{p}_t$ and $\mathbf{p}_{t+1}$ include reservation prices (bringing demand to zero) for products that are unavailable at t or $t+1$. The baseline approach used by most statistical agencies assumes homothetic utility, implying that all households have the same expenditure shares across products and experience the same inflation rate, which does not depend on U.

If we could estimate the parameters of the utility function, or expenditure function, the problem of inflation measurement would be solved. With N goods, using a flexible second-order approximation to utility would require estimation of about $\frac{N^2}{2}$ parameters. With $N = 50{,}000$, a lower bound for the number of products actually observed by statistical agencies, we would need to estimate 1.25 billion parameters, which is infeasible. As a result, the literature has developed approximations, using either statistical price indices with desirable axiomatic properties (e.g., Paasche, Laspeyres, and Fisher price indices) or price indices derived from utility functions governed by a small number of parameters [e.g., constant elasticity of substitution (CES) utility].[1]

An extensive literature has developed exact price indices or approximations grounded in homothetic utility functions. A simple approach to leverage these standard price indices while accommodating heterogeneity in inflation rates across household groups is to posit the existence of separate homothetic price indices for each group. Here we discuss this approach for price indices addressing biases arising from expenditure switching, entry and exit, and taste shocks.

Since at least the work of Gerschenkron (1947), we know that expenditure switching can be an important source of bias, because optimizing consumers tend to reallocate their expenditure toward products that become less expensive over time. To compute inflation for the set of continuing products indexed by k, available at both t and $t+1$, the following price indices can be

[1] For a survey of the early history of price index research, readers are referred to Diewert (1993).

used,

$$1+\pi_{t,t+1}^{\text{Laspeyres},b} \equiv \frac{\sum_k q_{k,t}^b \times p_{k,t+1}^b}{\sum_k q_{k,t}^b \times p_{k,t}^b} = \sum_k s_{k,t}^b \times \frac{p_{k,t+1}^b}{p_{k,t}^b},$$

$$1+\pi_{t,t+1}^{\text{Paasche},b} \equiv \frac{\sum_k q_{k,t+1}^b \times p_{k,t+1}^b}{\sum_k q_{k,t+1}^b \times p_{k,t}^b} = \left(\sum_k s_{k,t+1}^b \times \frac{p_{k,t}^b}{p_{k,t+1}^b}\right)^{-1},$$

$$1+\pi_{t,t+1}^{\text{Fisher},b} \equiv \sqrt{\left(1+\pi_{t,t+1}^{\text{Laspeyres},b}\right) \times \left(1+\pi_{t,t+1}^{\text{Paasche},b}\right)},$$

$$1+\pi_{t,t+1}^{\text{Tornqvist},b} \equiv \Pi_k \left(\frac{p_{k,t+1}^b}{p_{k,t}^b}\right)^{\frac{s_{k,t}^b+s_{k,t+1}^b}{2}},$$

$$1+\pi_{t,t+1}^{\text{CES},b} = \Pi_k \left(\frac{p_{k,t+1}^b}{p_{k,t}^b}\right)^{\omega_{k,t,t+1}^b},$$

where we have $\omega_{k,t,t+1}^b = \frac{\left(s_{k,t+1}^b - s_{k,t}^b\right)/\left(ln(s_{k,t+1}^b)-ln(s_{k,t}^b)\right)}{\sum_k\left[\left(s_{k,t+1}^b - s_{k,t}^b\right)/\left(ln(s_{k,t+1}^b)-ln(s_{k,t}^b)\right)\right]}$; b indexes household groups (e.g., income quintiles); $p_{k,t}^b$ is the price paid by group b; $q_{k,t}^b$ is the quantity purchased; and $s_{k,t}^b$ is the spending share out of total expenditure on continued products.[2] Inflation rates can vary across household groups due to heterogeneity in expenditure shares and prices paid.

These price indices assign different weights to product-level price changes, which handles substitution differently. The Laspeyres index uses expenditure shares at t, which does not allow consumers to substitute and tends to overstate true inflation. The Paasche index uses shares at $t+1$, which tends to understate inflation. The Fisher and Törnqvist indices are natural benchmarks because they are superlative indices, treating prices and quantities equally across periods and providing a second-order approximation to twice continuously differentiable, homothetic expenditure functions (e.g., Diewert 1976). However, they cannot account for the change in cost of living caused by the entry and exit of goods over time.

The CES index is of particular interest because it can be adjusted in a simple way to measure the inframarginal consumer surplus created by product entry or destroyed by exit. Following Feenstra (1994), we can write the inflation rate accounting for product entry and exit as

$$1+\widetilde{\pi}_{t,t+1}^{\text{CES},b} = \left(1+\pi_{t,t+1}^{\text{CES},b}\right) \times \left(\frac{1-s_{N,t+1}^b}{1-s_{E,t}^b}\right)^{\frac{1}{\sigma^b-1}},$$

where $s_{N,t+1}^b$ is the spending share on new products (available at time $t+1$ but not at time t), $s_{E,t+1}^b$ is the spending share on exiting product (available at time t but no longer at time $t+1$), and σ^b is the elasticity of substitution between products for household group b.

Accounting for product entry and exit is challenging, because prices are not observed when a product is not available. By assuming a functional form for utility, one can infer the change

[2]For more details on the CES price index, readers are referred to Sato (1976) and Vartia (1976). Note that the Sato–Vartia weights $\omega_{k,t,t+1}^i$ are bounded between $s_{k,t}^i$ and $s_{k,t+1}^i$.

in consumer surplus from the observed spending shares on new products and products about to exit, provided that consumers' elasticities of substitution are known.[3] The second term in the expression above lowers inflation if there is net entry, that is, $s^h_{N,t+1} > s^h_{E,t}$.

Crawford & Neary (2019) apply a similar approach to address entry and exit in characteristic space rather than in product space, and Feenstra & Weinstein (2017) derive the correction for entry and exit under translog preferences, which allow for finite reservation prices and varying demand elasticities, contrary to CES.[4]

A more recent, emerging literature relaxes the assumption of time-invariant tastes that underlies the preceding price indices. Redding & Weinstein (2020) develop an approach using CES preferences and considering mean-zero taste shocks. They show that relative taste shocks tends to introduce an upward bias in the standard CES price index.[5] Intuitively, consumers reallocate their expenditure toward products for which tastes increase, and the standard CES price index fails to capture the fact that products with increasing expenditure shares tend to have lower taste-adjusted prices.

Inflation rates could in principle differ across household groups, whose expenditure shares vary across the product space and which may pay different prices for the same product. Using separate homothetic price indices for each group is a convenient approach to investigate inflation heterogeneity, and in particular to assess the importance of expenditure switching, entry and exit, and taste shocks.[6] Indexing by h individual households rather than groups, the same formulas can be used to investigate household-level heterogeneity in inflation rates, which may occur even within groups thought to be homogeneous (e.g., within income deciles or age groups).

2.2. Non-Homothetic Preferences

A principled approach to studying inflation inequality is to use a non-homothetic utility function in which expenditure shares and the price index vary with the level of utility. Building on early contributions by Gorman (1965) and Hanoch (1975), Comin et al. (2021) show that non-homothetic CES preferences (nhCES) are especially convenient to study secular sectoral trends in inflation and expenditure. Matsuyama (2019) show that nhCES is tractable enough to be embedded in a model with endogenous technological change and trade, which are two leading candidate causes for inflation inequality.

NhCES preferences over products indexed by k are characterized by a utility function $U \equiv F(\mathbf{q})$ defined implicitly through the constraint

$$\sum_k \Omega_k^{\frac{1}{\sigma}} \left(\frac{q_{k,t}}{g(U)^{\varepsilon_k}} \right)^{\frac{\sigma-1}{\sigma}} = 1,$$

[3] Nevo (2003) discusses the sensitivity of price indices with new products to assumptions about the demand system.

[4] Diewert et al. (2020) derive analytical formulas for the biases from entry and exit for standard statistical indices, including Fisher and Törnqvist indices, in terms of unobserved reservation prices.

[5] Redding & Weinstein (2020) also show that their approach can be implemented with other invertible demand systems, including non-homothetic CES, translog, and almost ideal demand system.

[6] In high-frequency studies (e.g., Ivancic et al. 2011), chain drift is another source of bias that may differ across household groups. For a discussion of other potential biases in the US Consumer Price Index (CPI), readers are referred to Hausman (2003). The price indices discussed in this section can also be used to compute purchasing power parity (PPP) indices across countries (see Deaton & Heston 2010 for a recent review).

where $q_{k,t}$ are quantities consumed, and $g(.)$ is any positive-valued, continuously differentiable, and monotonically increasing function.[7]

Hicksian demand is $q_{k,t} = \Omega_k\left(\frac{p_{k,t}}{e^{\text{nhCES}}(U,\mathbf{p})}\right)^{-\sigma} g(U)^{(1-\sigma)\varepsilon_k}$, so the expenditure function for utility level U and price vector $\mathbf{p}$ can be written as $e^{\text{nhCES}}(U,\mathbf{p}) \equiv \sum_k p_k q_k = \left[\sum_k \Omega_k^{\frac{1}{\sigma}} g(U)^{(1-\sigma)\varepsilon_k} p_{k,t}^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$. This expression is identical to homothetic CES, except for the term $g(U)^{(1-\sigma)\varepsilon_k}$. Ω_k is the standard taste parameter, while $g(U)^{(1-\sigma)\varepsilon_k}$ is the nonhomothetic taste shifter, which depends on the level of utility U. Each product has a non-homotheticity parameter ε_k that governs the slope of utility Engel curve.

NhCES has two noteworthy properties. First, the elasticity of the relative demand for two products with respect to a monotonic transformation $g(.)$ is constant: $\partial log(q_i/q_j)/\partial log(g(U)) = (1-\sigma)(\varepsilon_i - \varepsilon_j)$. Second, the elasticity of substitution between different products is constant: $\partial log(q_i/q_j)/\partial log(p_j/p_i) = \sigma$. These properties make nhCES particularly tractable for structural analyses of secular macroeconomic trends or trade patterns, which are discussed near the end of this article.

Using nhCES and other non-homothetic utility function to compute inflation inequality is an important direction for future research. Comin et al. (2021) show how to estimate the nhCES parameters from observed prices and expenditure shares. Using the estimated parameters, one can compute the change in the cost of reaching utility level U between t and $t+1$ as

$$1 + \pi_{t,t+1,U}^{\text{nhCES}} \equiv \frac{e^{\text{nhCES}}(U,\mathbf{p}_{t+1})}{e^{\text{nhCES}}(U,\mathbf{p}_t)} = \left(\frac{\sum_k \Omega_k^{\frac{1}{\sigma}} g(U)^{(1-\sigma)\varepsilon_k} p_{k,t+1}^{1-\sigma}}{\sum_k \Omega_k^{\frac{1}{\sigma}} g(U)^{(1-\sigma)\varepsilon_k} p_{k,t}^{1-\sigma}}\right)^{\frac{1}{1-\sigma}}.$$

Compared with the formulas discussed in Section 2.1, this expression allows for a continuous analysis of price indices across the household income distribution. More flexible utility functions could be used—for example, nested nhCES.

Recent work by Almås et al. (2018) and Atkin et al. (2020) provides a flexible approach to non-homothetic price index estimation, extending the Engel curve approach of Costa (2001) and Hamilton (2001). In particular, Atkin et al. (2020) show that income-specific price index and welfare changes can be estimated nonparametrically if preferences are quasi-separable and changes in relative prices are observed for a subset of products.

2.3. Directions for Future Work

The substantial progress made by the price index literature in recent years provides clear guidance for empirical work on inflation inequality. It is crucial to estimate expenditure shares, effective prices paid, spending shares on new and exiting goods, and demand elasticities—all of which may vary across households, and in particular along the income distribution.

Two areas that are potentially central for inflation inequality appear to have remained largely underexplored in the price index literature. First, the price indices reviewed above are based on static models of consumption. Many purchases have implications over long time horizons—for example, buying a home. In the context of the secular decline in interest rates, a key task for future work would be to develop dynamic price indices accounting for intertemporal substitution bias

[7]The utility function $U(.)$ is globally monotonically increasing and quasi-concave if $\sigma > 0$ and $\sigma \neq 1$, $\Omega_k > 0$, and $\varepsilon_k > 0$ for all k.

and changes in intertemporal prices, and allowing for heterogeneity across household groups.[8] Such indices could in particular improve our understanding of inequality between renters and homeowners.[9]

Second, consumer optimization is the linchpin of all price indices. Mounting evidence from behavioral economics suggests that consumers in fact often fail to optimize, and that these failures may systematically correlate with household income (e.g., Handel et al. 2020). Given the high price dispersion for identical items observed in micro data (e.g., Kaplan et al. 2019), developing behavioral price indices allowing for optimization frictions and costly consumer search would be an important direction for future work, although one that would depart more fundamentally from the established literature. Malmendier & Nagel (2016), Cavallo et al. (2017), and D'Acunto et al. (2021) show the empirical relevance of behavioral models of inflation expectations, highlighting the roles of information frictions, rational inattention, and adaptive learning.

3. MEASURING INFLATION INEQUALITY

This section discusses recent findings on the measurement of inflation inequality over a long horizon or at a business cycle frequency.

3.1. Long-Run Trends

A growing literature measures inflation inequality, using either survey data available from statistical agencies and covering the full consumption basket or proprietary micro data for specific sectors. Because spending patterns across household groups differ primarily within industries, rather than across, it is important to use granular data. Earlier work on inflation inequality—for example, by Amble & Stewart (1994), Garner et al. (1996), Crawford & Smith (2002), Hobijn & Lagakos (2005), and McGranahan & Paulson (2006)—suggests that differences in inflation rates across household groups are modest. More recent work shows that substantial differences arise, in particular across income groups, with more detailed data that help alleviate aggregation bias.

Jaravel (2019) measures inflation inequality using a linked data set covering the full consumption basket of US households from 2004 to 2015. Spending shares are measured using the Consumer Expenditure Survey (CEX), whereas price changes at the level of product categories are available from the Consumer Price Index (CPI) data series.[10] The matched data set (CEX-CPI) provides 256 detailed product categories.

The results across deciles of the household income distribution are reported in **Figure 1*a***.[11] Inflation declines linearly across income deciles. Between 2004 and 2015, average annual

[8] Reis (2009) proposes a dynamic price index for a representative agent, and Osborne (2018) develops a price index for storable goods.

[9] Bajari et al. (2005) study the welfare effects of housing inflation with a representative agent, developing a compensating variation approach that keeps expected discounted utility constant given a change in current house prices.

[10] The CEX and CPI data sets can be found, respectively, at **https://www.bls.gov/cex/pumd.htm** and **https://www.bls.gov/cpi/data.htm**.

[11] For comparability with the Nielsen scanner data discussed below, which only keep track of discrete income bins, it was necessary to pull together the seventh and eighth income deciles, as well as the ninth and tenth income deciles. During the sample, the thresholds separating the deciles of the household income distribution up to the sixth decile were approximately \$10,000, \$20,000, \$30,000, \$40,000, \$50,000, and \$60,000; the seventh and eighth decile cover the range \$60,000–\$100,000, and the ninth and tenth deciles are above \$100,000.

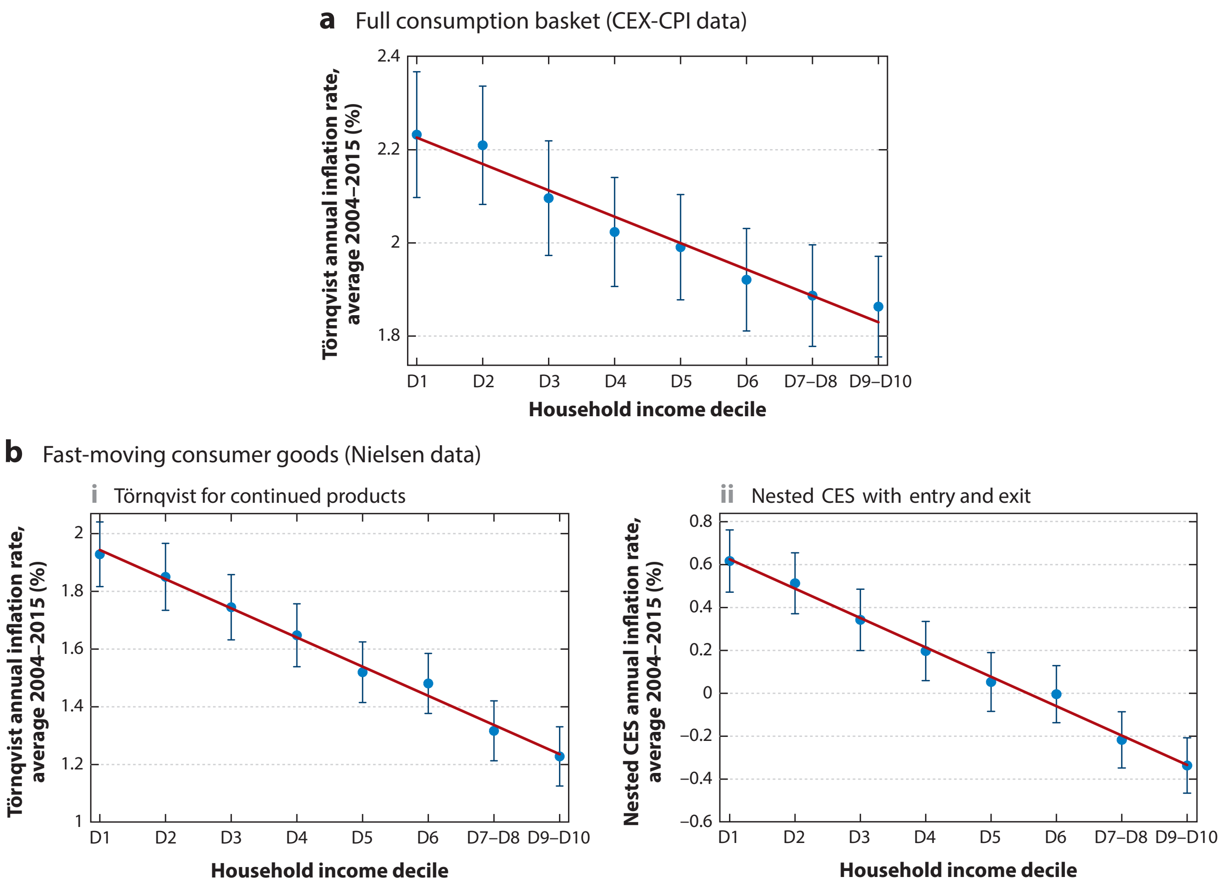

Figure 1

Inflation inequality in the United States (2004–2015). Panel *a* measures Törnqvist inflation in the CEX-CPI data, covering the full consumption basket. In panel *b*, subpanel *i* reports Törnqvist inflation for continued products across household income deciles for fast-moving consumer goods covered in the Nielsen data. Subpanel *ii* uses the nested CES price index, taking into account changes in product variety. Abbreviations: CES, constant elasticity of substitution; CEX, Consumer Expenditure Survey; CPI, Consumer Price Index: D, decile. Figure adapted with permission from Jaravel (2019).

Törnqvist inflation was 1.86% for the fifth income quintile, while it was 2.20% for the first income quintile. The average annual inflation difference between the top and bottom income quintiles is 0.346 percentage points [standard error (SE) = 0.0476]. This different remains similar with other price indices: 0.368 (SE = 0.0502) for Laspeyres, 0.349 (SE = 0.0480) for Paasche, and 0.349 (SE = 0.0435) for CES. The magnitude of inflation inequality is substantial compared to the biases in the measurement of aggregate inflation that have been studied in the literature.[12]

[12]For example, the 1996 Boskin Commission Report estimated the magnitude of substitution bias to be about 0.40 percentage point per year (Boskin 1996).

Table 1 Inflation inequality and aggregation bias: full consumption basket (CEX-CPI data)

Aggregation level	Δ Inflation rates	
	pp	% Explained
Detailed categories $N = 256$	0.3464	100
Subcategories $N = 22$	0.0739	21.3
Main categories $N = 11$	0.0965	27.8

The table decomposes the inflation difference between the top and bottom income quintiles. Abbreviations: CEX, Consumer Expenditure Survey; CPI, Consumer Price Index; pp, percentage point. Table adapted with permission from Jaravel (2019).

Table 1 examines at what level of product aggregation inflation inequality arises, using a standard within-between decomposition.[13] The full inflation difference between the top and bottom income quintiles is measured across the most detailed product categories, with $N = 256$. Measured inflation inequality falls by about 80%, to 0.0738 percentage points a year, when considering the "between" component across subcategories, with $N = 22$. Likewise, the inflation difference arising across the main product categories, with $N = 11$, is only 0.0965 percentage points a year. These results show that aggregation bias can be severe but substantial inflation inequality can be measured with standard survey data, without the need to resort to proprietary data.

Jaravel (2019) also measures inflation inequality between 2004 and 2015 using Nielsen scanner data.[14] The data cover fast-moving consumer goods—products with barcodes, including food products, household supplies, and health and beauty products—which account for about 30–40% of expenditure on goods, or about 15% of total expenditure. The results are reported in **Figure 1*b***. Subpanel *i* shows the results for continued products: Annual inflation for retail products was 0.661 (SE = 0.0535) percentage points higher for the bottom income quintile relative to the top quintile. Subpanel *ii* includes changes in product variety over time, using the CES correction term for expanding product variety as done by Feenstra (1994). Inflation inequality increases to 0.8846 (SE = 0.0739) percentage points a year.

The within-between decomposition for the scanner data is reported in **Table 2**. Columns 1 and 2 report the decomposition for inflation for continuing products, whereas columns 3 and 4 focus on the welfare effects of changes in product variety. A significant fraction of inflation inequality arises at a very detailed level, within the 1,042 very detailed product categories defined in the Nielsen data and called "product modules." Almost no inflation inequality can be detected at the level of the 10 broad departments defined by Nielsen.[15]

[13] For any grouping of products G, the inflation difference between two household groups, e.g., the top and bottom income quintiles, can be decomposed as (Diewert 1976)

$$\pi^T - \pi^B \equiv \sum_G s_G^T \pi_G^T - \sum_G s_G^B \pi_G^B = \underbrace{\left(\sum_G s_G^T \pi_G - \sum_G s_G^B \pi_G\right)}_{\text{Between}} + \underbrace{\sum_G \overline{s_G}(\pi_G^T - \pi_G^B)}_{\text{Within}},$$

with s_G^i denoting the share of spending of income group i on product grouping G, and π_G^i denoting the inflation experienced by income group i in product grouping G. π_G and $\overline{s_G}$ denote the average inflation rate and the average spending shares for product grouping G, respectively.

[14] Nielsen data are proprietary but can be accessed for research purposes through the University of Chicago at **https://www.chicagobooth.edu/research/kilts/datasets/nielsen**.

[15] The fourth row of **Table 2** focuses on the inflation inequality that arises across barcodes (0.541 percentage points), excluding the inflation difference arising from the effective prices paid for the same barcode by different income groups. The price channel increases inflation inequality to 0.661, as in **Figure 1**.

Table 2 Inflation inequality and aggregation bias: fast-moving consumer goods (Nielsen data)

Aggregation level	Δ Inflation rates, continuing products		Δ Log Feenstra, variety adjustment	
	pp	% Explained	pp	% Explained
	(1)	(2)	(3)	(4)
Barcodes $N = 2{,}240{,}278$	0.541	100	1.487	100
Product modules $N = 1{,}042$	0.358	66.2	0.578	38.9
Departments $N = 10$	0.071	13	−0.048	−3.3

The table decomposes the inflation difference between the top and bottom income quintiles in the Nielsen data, covering fast-moving consumer goods. Abbreviation: pp, percentage point. Table adapted with permission from Jaravel (2019).

The available evidence thus indicates that inflation inequality can be large and sustained over at least a 10-year period. This finding has potential implications for the indexation of the poverty line, welfare benefits, and tax brackets. In a recent policy brief using the estimates of Jaravel (2019), Wimer et al. (2019) reestimate recent trends in poverty and income inequality from 2004 to 2018. The adjusted inflation index indicates that 3.2 million more people are classified as living in poverty in 2018, and that real household income for the bottom 20% of the income distribution actually declined by nearly 7% since 2004 (instead of a decline of about 1% with official CPI). These results suggest that inflation inequality could significantly accentuate both the incidence of poverty and real income inequality. The indexation of food stamps provides another telling example. Between 2004 and 2015, food CPI indexation implied an increase in nominal food stamp benefits of 23.19%. In contrast, indexation on the price index for food-stamp eligible households implies a 31.44% increase, because food-stamp eligible households experienced higher inflation rates (using estimates from Jaravel 2018).

Recent work analyzes many other important dimensions of inflation inequality across households. First, using Nielsen scanner data, Kaplan & Schulhofer-Wohl (2017) show that there is a lot of heterogeneity in inflation rates at the household level, even within income groups. In Nielsen data, households' inflation rates have an annual interquartile range of 6.2 to 9.0 percentage points.

Second, a growing literature studies disparities in inflation rates across both cities and income groups. Moretti (2013) documents that college graduates experience larger increases in the cost of living because they increasingly concentrate in cities with high cost of housing. This finding suggests that the increase in the real (i.e., utility) college wage premium since 1980 may be smaller than the nominal increase. Diamond (2016) overturns this result by showing that amenities improved endogenously in high-skill cities. She estimates that the increase in amenities was such that the real college wage premium in fact increased more than the nominal premium. In related work, Handbury (2019) uses scanner data to show that there are large differences in how wealthy and poor households perceive the choice sets available in wealthy and poor cities. Estimating a non-homothetic demand system, she finds that, relative to low-income households, high-income households enjoy 40% higher utility per dollar of expenditure in wealthy cities relative to poor cities. Most of this variation is explained by differences in product variety across locations rather than by differences in price for identical items.

In sum, there is an emerging empirical consensus around the idea that inflation varies across the income distribution as well as across locations. The increased availability of micro data, in particular scanner data, was key in reaching this conclusion, because expenditure patterns differ at granular levels, and micro data are necessary to measure inflation inequality to its full extent. The literature has also shown that changes in product variety and amenities, which are typically overlooked by statistical agencies, can have important implications for inflation inequality. Despite substantial progress, much remains to be done to obtain a comprehensive picture of inflation inequality over longer periods of time,[16] using micro data in sectors other than fast-moving consumer goods and in countries other than the United States.[17]

3.2. High-Frequency Studies

An emerging literature studies inflation inequality at a high frequency. Because inflation inequality is typically small in any single year, the measurement of long-term trends discussed previously is a central task to assess to what extent inflation inequality compounds over time. However, it is also potentially important to track inflation inequality during major economic crises, in order to assess whether purchasing power is eroded for the most vulnerable and to adjust low-income support programs accordingly. For example, Argente & Lee (2020) show that inflation was significantly higher for low-income households during the Great Recession of 2008 in the United States.

In recent work, Cavallo (2020) and Jaravel & O'Connell (2020b) provide real-time measurement of inflation inequality during the COVID-19 pandemic. Cavallo (2020) uses data from credit and debit transactions in the United States, available at the level of broad sectors, to update the expenditure weights used to compute CPI. Because of social distancing restrictions, households spend relatively more on food and other categories with higher inflation, and less on deflationary categories such as transportation. Accounting for these expenditure switching effects, Cavallo (2020) finds that the inflation rate is higher than the official CPI because of expenditure switching effects. Moreover, relative prices across sectors changed significantly during the pandemic. Independently of expenditure switching, low-income households have higher baseline expenditure shares on food and other categories with higher inflation, and as a result they experienced more inflation during this period, as shown in **Figure 2*a***. Specifically, low-income households had an annual inflation rate of 1.12% in May 2020, compared to just 0.57% for high-income households.

In contrast, using real-time scanner data for the United Kingdom covering fast-moving consumer goods, Jaravel & O'Connell (2020a) find little evidence of inflation inequality arising within this subset of products. **Figure 2*b*** shows that inflation increased markedly at the beginning of the lockdown in the United Kingdom, but this increase was very similar across expenditure quartiles. If anything, inflation was slightly lower for low-income households. This slight difference can be traced to the differential use of promotions across groups. Much of the increase in inflation during the lockdown came from a fall in the frequency of promotions, which was slightly less consequential for low-income households, who tend to buy fewer items on promotion in normal times. Furthermore, Jaravel & O'Connell (2020b) compute household-level price indices and find that 96% of UK households have experienced inflation in 2020, whereas in prior years around 50% of households had experienced deflation. Younger households experienced lower inflation than older households. These differences may become important for purchasing power dynamics if

[16]Jaravel (2019) extends the CEX-CPI data discussed above to obtain coverage going back to 1953. Doing so requires using less-detailed product categories (48 instead of 256). Inflation inequality persists over the long run. However, consistent with the results presented above on the role of aggregation bias, measured inflation inequality is smaller in this sample with coarser categories.
[17]Using household surveys in India, Almås & Kjelsrud (2017) find that the relative price changes during most of the period from 1993 to 2012 were pro-poor and significantly reduced inequality in India. In recent work, Beck & Jaravel (2020) measure inflation inequality in the 2010s using scanner data in a panel of 34 countries, and they find that in most countries inflation was higher for lower-income households, including in developing countries.

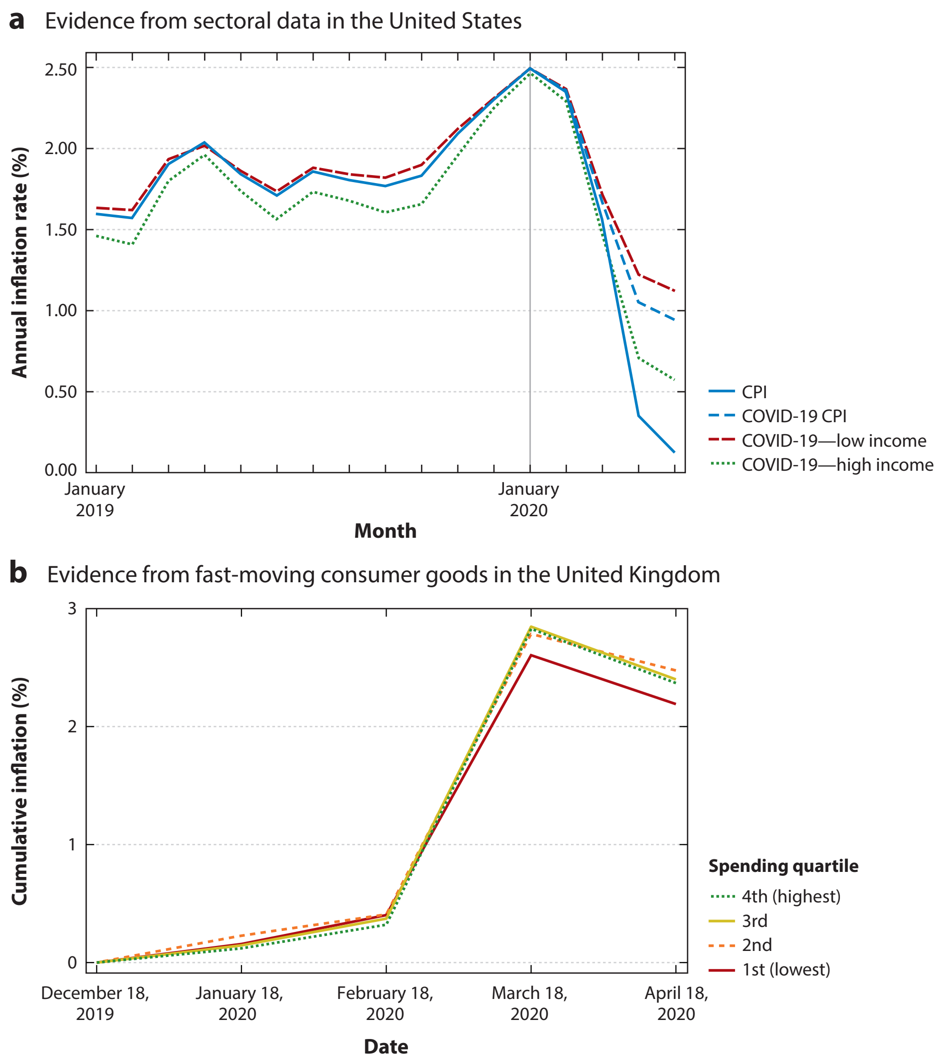

Figure 2

Real-time inflation inequality during the Great Lockdown. Panel *a* reports the annual inflation rate from January 2019 to May 2020 in the United States. The CPI uses standard expenditure weights, whereas the COVID-19 CPI indices use real-time expenditure weights obtained from credit card data. Panel adapted with permission from Cavallo (2020). Panel *b* reports the cumulative inflation rate from December 2019 to May 2020 by quartiles of the household expenditure distribution, using scanner data in the United Kingdom. Panel adapted with permission from Jaravel & O'Connell (2020a). Abbreviation: CPI, Consumer Price Index.

they persist and compound over time, but in the short run they are modest relative to the increase in aggregate inflation.

Increased reliance on private sector data, for example from credit and debit transactions or scanner data, is a useful avenue to improve the ability of statistical agencies to diagnose inflation risks in real time during economic crises, including inflation inequality. In particular, scanner data make it possible to measure changes in product variety, in effective prices paid (including promotions), and in item-level expenditure shares across sociodemographic groups.

3.3. Directions for Future Work

The existing literature leaves open several important directions for further work on the measurement of inflation inequality.

First, the large magnitude of aggregation bias highlights that it is crucial to eventually obtain micro data for each sector of the economy to accurately measure effective prices paid, expenditure shares, and product variety across sociodemographic groups. Whereas the literature has used scanner data for fast-moving consumer goods extensively, the next generation of empirical studies of inflation inequality could leverage alternative data sources on other sectors.

For example, commercial data sets on automobiles, real estate properties, or slow-moving consumer goods could prove very useful. For housing, Nowak & Smith (2020) develop new quality-adjusted house price indexes for the United States, which could be leveraged to study inflation inequality. For health care, claims data sets provide very rich information. In ongoing work, Jaravel et al. (2020) document inflation inequality in health care using comprehensive claims data for Utah from 2012 to 2015. They find that there was higher inflation for the treatment of conditions that affect low-income groups more, another source of inflation inequality. Inflation inequality could also be measured for digital "free" goods, including Google, Skype, Wikipedia, maps, messaging, music, and all smartphone apps. Large-scale online choice experiments could be used for this purpose, as done by Brynjolfsson et al. (2020).[18] Another important endeavor is to improve the measurement of inflation inequality for the service sector, where large-scale micro data on quantities and prices appear to be lacking at present.

A second promising direction is to think about inflation inequality in the context of PPP indices across countries. Only a handful of studies, including those by Deaton et al. (2004) and Almås & Sorensen (2020), have attempted to compute income group–specific PPP indices, mostly using survey data. Much remains to be learned from micro data to address aggregation bias and to better measure global inequality. For example, using scanner data in a panel of 34 countries, Beck & Jaravel (2020) show that income group–specific PPP indices vary substantially from the representative-agent PPP indices.[19]

Third, most of the literature focuses on differences across income groups, age groups, and cities. It would be instructive to investigate inflation inequality with respect to other groups, for example by gender and race, or by focusing on the very top earners, such as the top 1% or 0.1%. We currently lack data to accurately describe expenditure and inflation patterns for the top earners, who are underrepresented in both traditional surveys and scanner data, even though they account for a substantial fraction of aggregate consumption.

4. WHAT ARE THE CAUSES OF INFLATION INEQUALITY?

This section presents recent evidence on two candidates causes for inflation inequality: endogenous technological change and trade.

4.1. Inflation Inequality and Endogenous Technological Change

A first potential driver of inflation inequality is the direction of technological change.

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[18]Using a randomized experiment, Allcott et al. (2020) show that deactivating Facebook leads to increased subjective well-being and reduced post-experiment valuations of Facebook, suggesting that standard elicited willingness-to-pay estimates for social media may overstate the actual consumer surplus.

[19]Almås (2012) and Argente et al. (2020) estimate PPP indices for a representative agent, using demand systems consistent with non-homotheticities, but do not estimate heterogeneity across the household income distribution.

4.1.1. Increasing returns to scale, market size, and the amplification of inequality. A long-standing literature on endogenous technological change suggests that market size creates incentives for innovation and entry. Larger markets induce more entry and could therefore benefit from larger product variety and lower prices, through both lower marginal costs of products and lower markups. The idea that higher or increasing market size leads to endogenous productivity gains goes back to the seminal work of Linder (1961) and Schmookler (1966), later formalized and extended in foundational contributions by Dixit & Stiglitz (1977), Krugman (1979), Shleifer (1986), Romer (1990), Aghion & Howitt (1992), Jones (1995a), Aghion & Howitt (1996), Acemoglu (2002), and Melitz (2003).

However, this extensive literature did not examine the implications of increasing returns and the market size channel for inequality. Recent work has made progress in estimating the causal relationship between market size and consumer prices, has linked changes in market size across product categories to changes in the (nominal) income distribution, and has quantified the implications for purchasing power inequality.

Jaravel (2019) examines whether the equilibrium response of supply to faster growth in demand from high-income consumers can explain the patterns of differential inflation and increase in product variety depicted in **Figure 1**. Because of economic growth and rising nominal income inequality, the market size for high-end (income-elastic) products increases faster than the market size for low-end (income-inelastic) products, which creates incentives for firm entry and higher product variety. This process can lead to a decrease in the price of existing products in the fast-growing and high-end market segments, because increased competitive pressure from new products pushes markups down. If the induced productivity gains are sufficiently large, this channel could amplify inequality.

4.1.2. Evidence for fast-moving consumer goods in the United States. Adapting the concepts developed by Acemoglu (2007) to examine sector-augmenting technical change, Jaravel (2019) tests both the weak bias and the strong bias hypotheses: When demand for a sector becomes relatively more abundant, does product entry endogenously increases in this sector (weak bias)? And is this effect sufficiently strong that the observed relative supply curves for goods are downward sloping (strong bias)? Using Nielsen data for fast-moving consumer goods, the answers turn out to be positive.

Tracing out the causal effect from market size to consumer prices is challenging because of reverse causality: Products with a lower quality-adjusted price will attract more consumers. To address this challenge, Jaravel (2019) uses a shift-share instrumental variable (IV) design leveraging changes in market size driven by US sociodemographic trends that are exogenous to price dynamics for fast-moving consumer goods. The IV design relies on two components: predetermined spending shares across the product space for a large number of sociodemographic groups, and heterogeneity in the population growth rates for these various groups during the sample period. Spending profiles across the product space are measured in the initial period and kept constant, such that the variation in the shift-share instrument comes entirely from changes in the size of the sociodemographic groups over time.

The results are depicted in **Figure 3**. The figure shows the reduced-form relationship between the shift-share instrument and inflation for continued products (panel *a*) and a CES price index taking into account the welfare effects of product entry and exit (panel *b*). The estimated effects are large: When the growth rate of demand increases by one percentage point, the IV estimates indicate that the inflation rate for products available in consecutive years falls by 0.42 percentage points (SE = 0.139). Accounting for changes in product variety, inflation falls by 0.62 percentage points (SE = 0.258). Using structural estimates of markups à la Hottman et al. (2016), over half

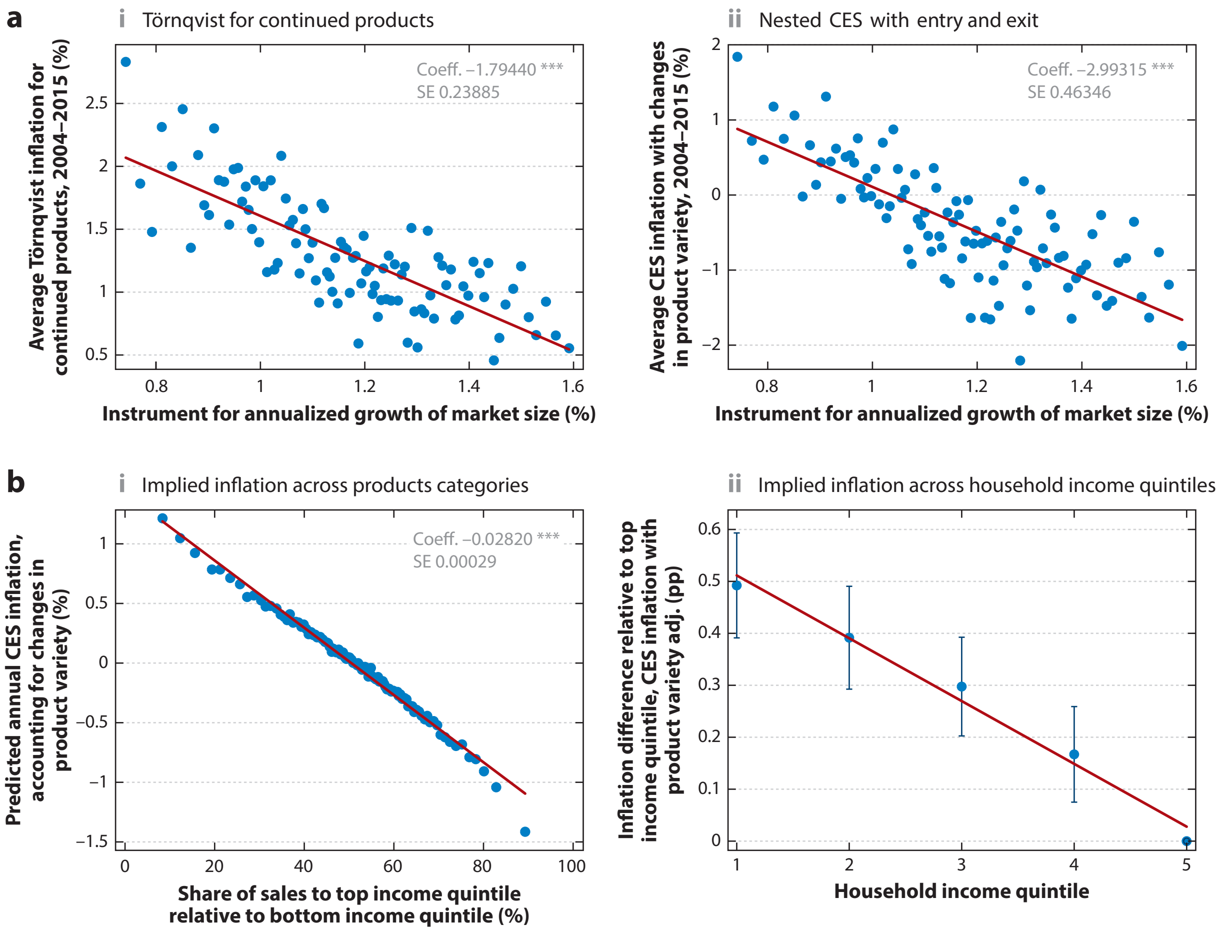

Figure 3

Inflation inequality and endogenous technological change. (*a*) Increased demand causes lower inflation (shift-share instrumental variable design). Subpanel *i* gives the relationship between the shift-share instrument for market size and a Törnqvist price index computed with products available across consecutive years. Subpanel *ii* gives the relationship with a nested CES price index accounting for product entry and exit across years. (*b*) Inflation inequality implied by changes in the US income distribution. Subpanel *i* reports the predicted impact of changes in market size (implied by changes in the US income distribution from 2004 to 2016) on inflation across product categories. The product categories are ranked by the share of sales to the top versus bottom income quintiles. Subpanel *ii* reports the implied inflation rates across household income quintiles, aggregating product-level price changes with quintile-specific expenditure weights. Three asterisks denote statistical significance at the 1% level. Abbreviations: CES, constant elasticity of substitution; Coeff., ordinary least squares regression coefficient; pp, percentage point; SE, standard error. Figure adapted with permission from Jaravel (2019).

of the impact on price for continued goods is found to result from falling markups rather than reduced marginal costs.[20]

To use these estimates to assess whether real inequality is amplified through the endogenous response of the product market to rising nominal inequality, it is important to first assess whether

[20]Regardless of the mechanism, the estimates show that the long-term supply curve is downward sloping in a reduced-form sense: As demand goes up, prices fall.

falling prices are driven by growing demand or merely by higher, but stagnating, demand.[21] In the latter case, the middle class would be the main beneficiary from the endogenous dynamics of technological change, because it still constitutes the largest market. Using an expanded shift-share IV design, Jaravel (2019) finds that the dynamics of supply are driven by changes in demand rather than by its level. As a result, high-income groups benefit from lower inflation.

Using these estimates, Jaravel (2019) computes the price index implications of changes in demand induced by changes in the income distribution from 2004 to 2016. If consumption patterns were very similar across income groups, the faster growth at the top would benefit society broadly through market size effects. Empirically, the difference in consumption baskets is such that the productivity gains from rising market size are unequally distributed. Subpanel *i* of **Figure 3*b*** shows that products (barcodes) that sell primarily to the top income quintile are predicted to experience a decline in prices of over 1%, compared to a 1% increase for products targeting the bottom quintile. In the same figure, subpanel *ii* shows the implications for the inflation rates experienced by different income quintiles, accounting for the fact that there is some overlap in consumption baskets across groups. The difference is substantial, with an annual inflation rate about 0.5 percentage points higher for the bottom quintile relative to the top quintile.

4.1.3. Evidence for other sectors and countries. A growing literature documents similar patterns for other sectors of the US economy, at the subnational level within the United States, and for other countries. There is thus an emerging empirical consensus that increasing demand leads to higher productivity and lower price indices, and that this channel can amplify rising nominal income inequality.

Acemoglu & Linn (2004) provide empirical evidence that market size influences entry of new drugs and US pharmaceutical innovation. Using national accounts data covering the entire US economy, Boppart & Weiss (2013) show that total factor productivity (TFP) growth is higher in more income-elastic sectors. Analyzing Nielsen scanner data across local markets, Handbury (2019) finds that the products and prices offered in the markets are correlated with local income-specific tastes. Leveraging data on durable good industries in the Chinese manufacturing sector, and using an IV design based on potential market size, Beerli et al. (2020) estimate that an increase in market size by 1% leads to a TFP increase of 0.46%.

Using Nielsen scanner data, Faber & Fally (2020) study an endogenous sorting channel whereby more productive firms cater to richer households in equilibrium. Estimating a quantitative model with household and firm heterogeneity, they show that rich households value higher-quality products significantly more, and that quality production features increasing returns to scale. These estimated economies of scale in quality production give larger firms incentives to sort into higher product quality, catering to the taste of richer households.

Focusing on housing and local amenities, Diamond (2016) and Couture et al. (2020) find that amenities adjust endogenously to local demand. The quantitative model of Couture et al. (2020) suggests that observed changes in the income distribution between 1990 and 2014 led to endogenous changes in neighborhood amenities and house prices that increased the welfare of richer households relative to low-income households, which amplified rising nominal income inequality.

[21]For example, Jones (1995b) develops a model in which it is the growth of market size, not its level, which drives innovation. Intuitively, if it becomes harder and harder to innovate as the market becomes larger, then a higher level of demand creates higher returns to research and development (R&D) but also higher costs of R&D—therefore, only additional growth of demand can induce more innovations.

The importance of market size and increasing returns has also received empirical support in recent studies leveraging trade data. Dingel (2017) uses micro data on US manufacturing plants and finds that home-market demand explains a significant fraction of the patterns of specialization and trade across US cities. Costinot et al. (2019) also find support for the home market hypothesis using drug sales data from the global pharmaceutical industry: Countries tend to be net sellers of the drugs they demand the most. Using trade shocks, Bartelme et al. (2019) estimate sector-level economies of scale. They find statistically significant scale elasticities in every two-digit manufacturing sector, with an average of 0.13 and substantial heterogeneity, and with sector-level estimates ranging from 0.07 to 0.25. Ding (2020) examines empirically whether a positive demand shock in one industry leads a multi-industry firm to increase its productivity and sales in other industries due to joint production; he estimates that the cross-spillovers are large and account for 20% of the aggregate response of prices to market size.

4.1.4. The distributional effects of the product cycle. The aforementioned studies all rely on the idea that products cater to segmented markets. However, an important feature of innovations is the so-called product cycle—the idea that new products initially benefit the rich but may eventually enter everyone's consumption baskets (e.g., Hayek 1931, Vernon 1966).

Eizenberg (2014) investigates the distributional aspects of the product cycle for central processing units (CPUs). According to the estimated quantitative model, Intel's introduction of its Pentium M chip contributed significantly to the growth of the mobile PC segment and to consumer welfare overall, but most of the benefits were captured by the 20% least price-sensitive consumers. Keeping older technologies on the shelf would have allowed the benefits from innovation to trickle down to price-sensitive households. Thus, endogenous exit of old technologies can be detrimental to the least well-off and contribute to inflation inequality. Investigating the effects of the product cycle on inequality in other sectors would be a fruitful direction for future research.

4.2. Inflation Inequality and Trade

International trade is another important channel that could lead to differences in inflation across income groups.

4.2.1. Heterogeneous expenditure shares on imports. A first strand of the recent literature investigates whether expenditure shares are heterogeneous across consumer groups, in particular along the income distribution.

Expenditure shares on imports are a key input in the distributional effects of trade. To a first-order approximation, by Roy's identity a fall in the price of foreign products will benefit relatively more those consumers who have larger expenditure shares on imports. A common view is that low-income households spend more on manufacturing and other traded products and therefore benefit more from trade via the expenditure channel. Leveraging new data, recent evidence overturns that conventional wisdom.

Measuring expenditure shares on imports across income groups is a conceptually simple task, but several challenges arise in practice. For one, it is important to measure direct imports but also indirect import spending via imported intermediate inputs, which are more difficult to track. Moreover, expenditure patterns on imports may differ across income groups within detailed sectors, highlighting the importance of micro data to avoid potential aggregation bias. The increased availability of data has helped address these challenges in recent work.

Borusyak & Jaravel (2018) study the United States using linked data sets that cover the consumption and production sides of the entire US economy, including expenditure micro data on consumer packaged goods and motor vehicles. Trade in intermediate goods is accounted for using the US Bureau of Economic Analysis input-output (IO) table.[22] For consumer packaged goods, products from the Nielsen Homescan Consumer Panel are matched to their manufacturers or distributors in the US Census and Customs micro data. For vehicles, expenditure patterns on brands of cars and sport utility vehicles (SUVs), observed in the Consumer Expenditure Survey, are linked to Ward's Automotive[23] statistics on US vehicle imports, as well as to the Census of Manufactures and Customs data, to account for imported vehicle parts. Consumer packaged goods and motor vehicles together cover about 40% of total expenditures on goods.

The findings are reported in **Figure 4*a***. Subpanel *i* shows the differences in import shares arising across the 389 industries available in the 2007 IO table. As a fraction of spending on total expenditure, total imports are very stable across the household income distribution, hovering between 12% and 13%. The spending shares on imports remain flat across trading partners. Using more aggregate industries available over a longer period of time, subpanel *ii* shows that the expenditure shares on imports have remained similar across groups between 2002 and 2015.

This finding may come as a surprise given the common view that low-income households should benefit more from trade because they have larger expenditure shares on goods relative to services. In fact, the flat patterns in **Figure 4*a*** are due to offsetting effects. Richer households do consume a larger share of services, which are mostly nontraded. But within goods, richer groups spend more on industries with higher import penetration rates, such as electronics (e.g., relative to food). These forces turn out to offset each other almost exactly, resulting in similar overall spending shares on imports across income groups. Furthermore, Borusyak & Jaravel (2018) find that within consumer packaged goods and motor vehicles, richer households spend relatively more on imported products. The results are depicted in **Figure 4*b***. Overall, the expenditure channel in the United States does not appear to be pro-poor: The distributional effects are limited, and if anything the benefits to richer groups are higher.

In line with this conclusion, Levell et al. (2017) calculate the share of food spending devoted to imported food across the household income distribution in the United Kingdom. They find that the total import intensity of households' food consumption ranges from 38.0% in the poorest decile to 38.8% in the richest. For 17% of total food grocery spending, Levell et al. (2017) observe the country of origin for each barcode. The barcode-level analysis also reveals that there is little difference in import shares across income groups. However, the authors find that there is substantial variation across different consumers within income groups. For example, although on average households spend about 35% of their beef, lamb, and pork spending on imported products, some households buy everything from overseas.[24]

[22]The US Bureau of Economic Analysis input-output data can be found at **https://www.bea.gov/industry/input-output-accounts-data**.

[23]The Ward's Automotive Yearbook can be found at **https://www.wardsauto.com/miscellaneous/wards-automotive-yearbook**.

[24]An alternative approach is to use aggregate trade data and a non-homothetic demand system to infer spending shares on imported products at a large scale in many countries. Fajgelbaum & Khandelwal (2016) do so using an almost ideal demand system along with aggregate statistics and model parameters that can be estimated based only on widely available bilateral trade and production data. They find that trade typically favors the poor, who concentrate spending in more traded sectors. However, Borusyak & Jaravel (2018) show that these predictions turn out to be specific to the almost ideal demand system. With non-homothetic CES, there is no evidence that trade is pro-poor, in line with the available micro data for the United States.

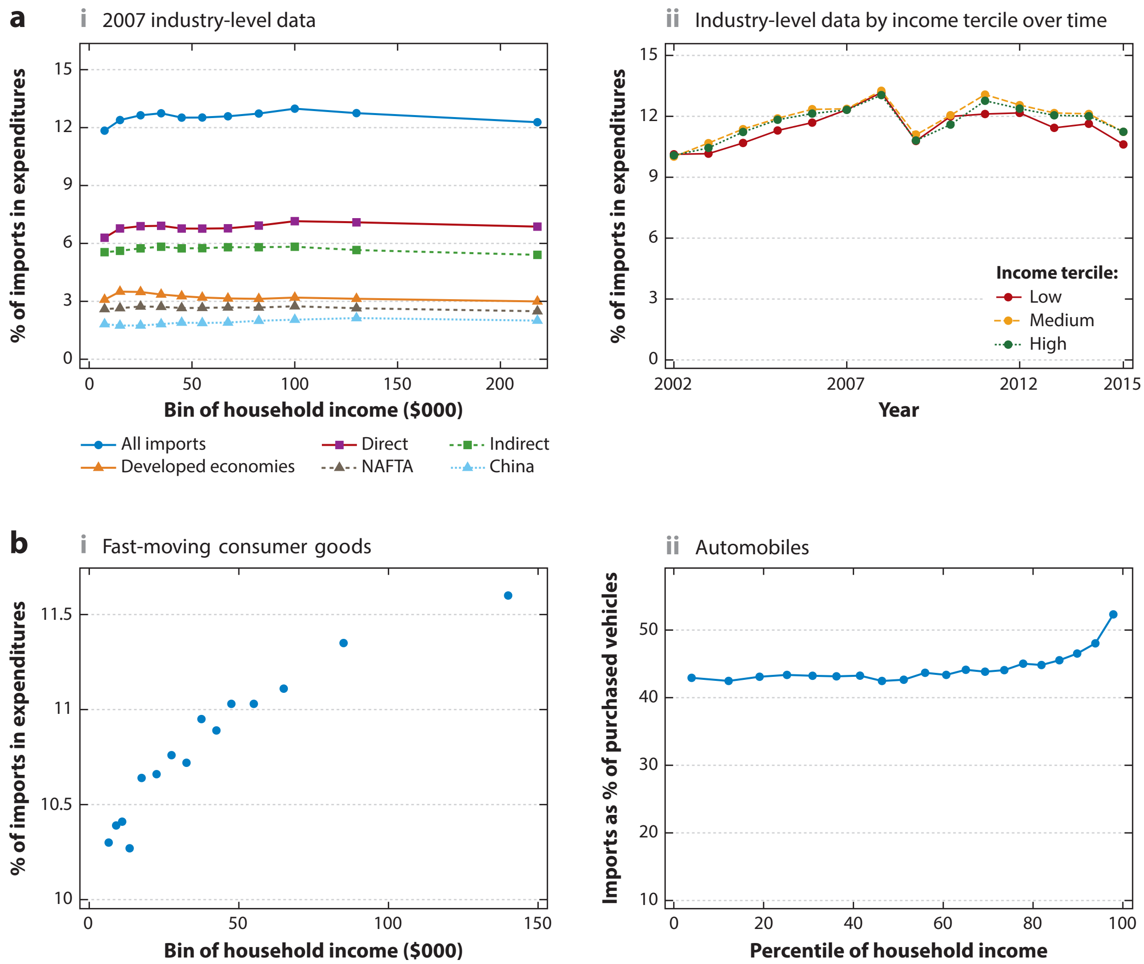

Figure 4

Inflation inequality and trade in the United States. Panel *a* reports spending shares on imports across the household income distribution for the full consumption basket, using industry-level data (CEX-IO). Subpanel *i* focuses on import shares in year 2007 for different trading partners across the income distribution; subpanel *ii* shows patterns over the long run by income terciles. Panel *b* reports spending shares on imports using micro data for (*i*) fast-moving consumer goods (Nielsen data) and (*ii*) automobiles (Ward's Automotive data). Abbreviations: CEX, Consumer Expenditure Survey; IO, input-output; NAFTA, North American Free Trade Agreement. Figure adapted from Borusyak & Jaravel (2018).

4.2.2. Evidence from trade and exchange rate shocks. A second strand of literature uses variation from major trade or exchange rate shocks to document the distributional effects across households via the expenditure channel. In addition to knowing the import shares across different types of goods, recent work shows that two other features matter for inflation inequality. First, it is necessary to estimate the pass-through rates of shocks into prices, which may vary depending on the shocks or the context. The pass-through rates of production costs and tariffs into prices depend notably on market structure and on firms' market shares, as shown recently by Auer &

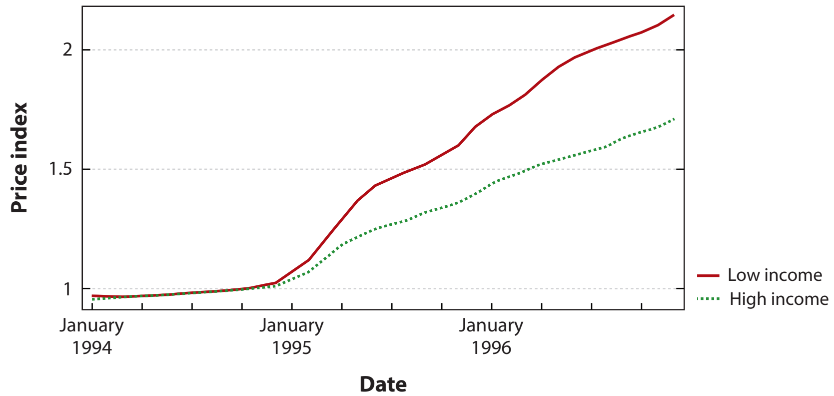

Figure 5

Inflation inequality after the 1994 Mexican devaluation. The high-income household consumes varieties priced above the median, and the low-income household consumes below the median within each product category. Figure adapted with permission from Cravino & Levchenko (2017).

Schoenle (2016), De Loecker et al. (2016), and Amiti et al. (2019).[25] Less is known about how inflation inequality may be affected by pass-through heterogeneity. Second, it is also important to estimate potential heterogeneity in the ability or willingness of households to substitute toward goods whose relative price falls more in response to shocks. Third, changes in product variety induced by trade may affect household groups differently. Recent studies focusing on various countries and time periods have helped advance the research frontier on these issues.

A growing literature studies exchange rate shocks and inflation inequality. Cravino & Levchenko (2017) study the 1994 Mexican devaluation. They estimate that the devaluation led to a fall in the relative price of tradeables and of lower-priced varieties within sectors. Because low-income households have higher expenditure shares on these products, their cost of living increased relatively more after the devaluation. The results are reported in **Figure 5**: Two years after the devaluation, the cost of living for the bottom income decile rose over 50% more than the cost of living for the top income decile. In the United Kingdom, Breinlich et al. (2019) study the impact of the depreciation of the pound sterling caused by the Brexit referendum. They find complete pass-through of import costs into consumer prices and estimate that there was little impact on inflation inequality. Income groups across the distribution were similarly affected, although there was substantial heterogeneity across households within income groups. More recently, Auer et al. (2021) study the impact of the 2015 Swiss Franc appreciation using scanner data. They find that low-income households substitute more between imports and domestic goods, implying that they benefit more (or lose less) from large changes in relative prices due to exchange rate or trade cost changes. They also show that households near the border lose less thanks to cross-border shopping. These studies show that the implications for inflation inequality can be large or small, depending on the context.

Other studies focus on productivity shocks abroad and their implications for consumers at home. A prominent example is the rise of imports from China to the United States in the 2000s and its implications for US consumer prices. Bai & Stumpner (2019) use scanner data and compute

[25] Studying the recent US–China trade war, Fajgelbaum et al. (2020) find complete pass-through of import tariffs into prices.

income-group specific price indices. They find that the China shock led to similar price declines for high- and low-income consumers. Using CPI micro data covering the full consumption basket, Jaravel & Sager (2019) find that the response of US consumer prices to the China shock was stronger in industries that cater to low-income households.[26] Hottman & Monarch (2020) study import price inflation by income deciles in the United States between 1998 and 2014. With a Laspeyres index, high- and low-income households experience similar import price inflation; but when allowing for sectoral expenditure switching, import price inflation is significantly higher for low-income households. They find no evidence of unequal inflation rates arising from trade with China.

Finally, recent studies examine trade liberalization episodes in developing countries. Using barcode-level microdata in Mexico, Faber (2014) shows that cheaper access to US imports reduces the relative price of higher-quality products in Mexican cities. This change leads to a significant increase in Mexican real income inequality, because empirically higher-income households in Mexico tend to buy products using higher-quality inputs. Using a nonparametric relative Engel curve, Atkin et al. (2020) find that India's trade reforms in the 1990s led to lower inflation for the rich.

Taking stock, these findings suggest that when considering inflation inequality, it is important to take into account other important channels—notably substitution, differential pass-through, and changes in product variety—in addition to heterogeneity in import shares. Depending on the context, the implications of trade for inflation inequality can be large. In some cases the rich experience lower inflation, in others the poor do. For the United States, despite some differences in methodologies and results across studies, a consistent picture emerges: Increased trade did not lead to substantial divergence in inflation rates across income groups over the past 20 years. This emerging empirical consensus contradicts the view—still widely held—that trade primarily reduces prices for the poor in the United States.

4.3. Directions for Future Work

Much remains to be learned about the impact on inflation inequality of technological change, openness to trade, and their interaction.

First, an important direction for future work is to document empirically the impact of new technologies on prices and consumer surplus by income groups. Much of the concern about the effects of new technologies on inequality focuses on the labor market, but it is important to document potential unequal gains via the expenditure channel. Although Section 4.1 made the case that endogenous technology dynamics tend to make innovations pro-rich, specific technologies may have different effects. For example, Aghion et al. (2020) document the price effects of automation and find that automation technologies tend to be used by firms that sell relatively more to low-income households, although the differences are modest. Fracassi et al. (2020) show that private equity firms help increase sales through the launch of new products, primarily in segments targeting high-income households. Calder-Wang (2019) studies the distributional impact of the gig economy, focusing on Airbnb and the housing market in New York. She finds that Airbnb leads to large losses for renters, as increased rental costs are not fully offset by increased rental choice. Moreover, the increased rent burden is larger for high-income, educated, and white

[26]Because imports from China account for a small share of total consumption, on the order of 2%, the impact on overall inflation inequality in the United States remains limited even when taking into account the differential pass-through into consumer prices.

renters because they prefer housing and location amenities that are most desirable to tourists. Many other technology shifts could be studied by leveraging existing data that have been used to study labor market outcomes. For example, Webb (2019) develops new measures of artificial intelligence patents, and Atkin et al. (2018) study the introduction of global retail chains in Mexico. Foreign retail entry leads to large welfare gains and pro-competitive effects, and the gains are larger for higher-income groups. New studies focusing on price effects and their distributional impacts have the potential to improve our understanding of technological innovations and of the consequences of regulating them.

Second, mechanisms other than market size may explain why the direction of innovation typically appears to favor the rich. For example, there is mounting evidence that access to innovation is very unequal: Women, minorities, and people from low-income backgrounds are underrepresented among patent inventors, entrepreneurs, and venture capitalists (see, e.g., Bell et al. 2019, Agarwal & Gaule 2020). This underrepresentation may have an impact on the direction of innovation, independent of market size. In recent work, Einiö et al. (2020) study the impact of peer effects on the direction of innovation, holding market size constant. Using quasi-experimental variation on exposure to peer groups at the university and during military service, they find that interacting with peers from low-income backgrounds leads entrepreneurs to shift toward innovating in necessities. This mechanism can help rationalize the empirical finding that innovators and entrepreneurs tend to target people like themselves. For example, entrepreneurs from high-income backgrounds tend to enter income-elastic industries (e.g., finance), whereas female entrepreneurs cater more often to female customers.

Third, a promising direction for future work is to think about the interaction between technology and trade. Recent contributions, including work by Sampson (2016) and Matsuyama (2019), emphasize that there is a rich and sometimes counterintuitive interplay between technology and trade. For example, one may think that the domestic demand composition becomes less important in an open economy, weakening some of the closed-economy dynamics described in Section 4.1. Matsuyama (2019) shows that the impact of domestic demand on the direction of domestic innovation may in fact be magnified in an open economy. Because of increasing returns to scale, the richer (poorer) country develops an endogenous comparative advantage in higher (lower) income elastic sectors. A fall in trade cost leads the richer (poorer) country to allocate even more resources toward higher (lower) income-elastic sectors by importing even more from the poorer (richer) country in lower (higher) income-elastic sectors. Hence, globalization can magnify the power of the differences in domestic demand composition in governing the patterns of innovation. Further empirical work on this question would be a useful contribution.

5. POLICY IMPLICATIONS

This section discusses several policy implications arising from the recent findings on inflation inequality discussed above.

5.1. Inflation Inequality and the Welfare Effects of Policies

Inflation inequality transforms the welfare effects of policies. Accordingly, the next generation of price indices, cost-benefit analyses, redistributive policies, and stabilization policies must take inflation inequality into greater consideration.

5.1.1. Measurement. As discussed in Section 3, an important priority for statistical agencies should be to obtain granular data in as many sectors as possible to keep track of income group–specific expenditure shares, prices paid, and changes in product variety. Scanner data, claims data, and other private sector data sets should prove very useful and could contribute more broadly to the measurement of inflation in real time.

Improving the measurement of inflation inequality is important to keep track of long-term trends and of the effects of various policy, technology, or trade shocks; but it also matters to accurately measure growth for the average citizen. Current practice, which uses aggregate expenditure shares, gives more weight to richer households, which account for a higher share of consumption. To the extent that inflation is lower for richer households, a plutocratic (expenditure-weighted) index will overstate real economic growth relative to a democratic (person-weighted) index.

5.1.2. Cost-benefit analysis. Given the growing empirical consensus that price indices can diverge across the income distribution, for cost-benefit analysis it it important to document more systematically the effects of policies on prices and consumer surplus. With the increased availability of price and expenditure data, the potential for heterogeneous price effects can be assessed for a wide range of policies, as illustrated by recent studies of carbon taxes (Bureau et al. 2019), import tariffs (Furman et al. 2017), rent controls (Diamond et al. 2019), the credit crunch (Kim 2021), soda taxes (Dubois et al. 2020), and food stamps (Hastings & Washington 2010, Jaravel 2018, Leung & Seo 2018).

Different approaches can be taken to aggregate heterogeneous effects into a single summary number to be used for cost-benefit analysis. For example, the empirical estimates of price effects can be plugged into a social welfare function. Alternatively, they can be used to compute agents' willingness to pay for the policy; willingness-to-pay estimates can then be aggregated across the income distribution, accounting for the distortionary cost of redistribution (as in Hendren 2020).

In some cases, the presence of non-homotheticities may affect the overall efficiency of a policy with a single representative agent and no distributional effects. For example, different sectors or firms may be subject to different inefficiencies because of the presence of market power and markups. In this case, it is important to assess whether product categories with higher distortions tend to have higher or lower income elasticities. If a policy tends to make agents richer, then it has a positive impact on efficiency if income-elastic sectors or firms have higher markups, because the policy leads to a reallocation of expenditures toward firms or sectors with higher distortions. Arkolakis et al. (2019) show that this channel tends to slightly reduce the gains from trade in a standard quantitative trade model.

5.1.3. Optimal taxation and redistribution. A recent line of work uses quantitative models to assess how endogenous prices and non-homotheticities should affect optimal tax policy.

Jaravel & Olivi (2019) study optimal redistributive taxation in a model à la Mirrlees (1971) with non-homotheticities, segmented markets, and increasing returns to scale. The presence of increasing returns to scale tends to substantially reduce the Laffer rate and optimal marginal tax rates. Furthermore, heterogeneity in consumption baskets affects the value of redistribution at different points of the income distribution. Redistribution to low-income households increases the market size of necessity products, whose price falls because of increasing returns to scale. As a result, the social marginal utility of redistributing an additional dollar to low-income groups increases, because they face lower prices and therefore a larger utility increase from additional spending. This endogenous increase in the value of redistribution at the bottom leads to more redistribution, which amplifies the price effects, hence the value of redistribution, and so on. This channel illustrates that, in general equilibrium, there can be a feedback loop between preferences for redistribution and prices. These effects can be quantitatively important, as reported in **Figure 6**. Relative

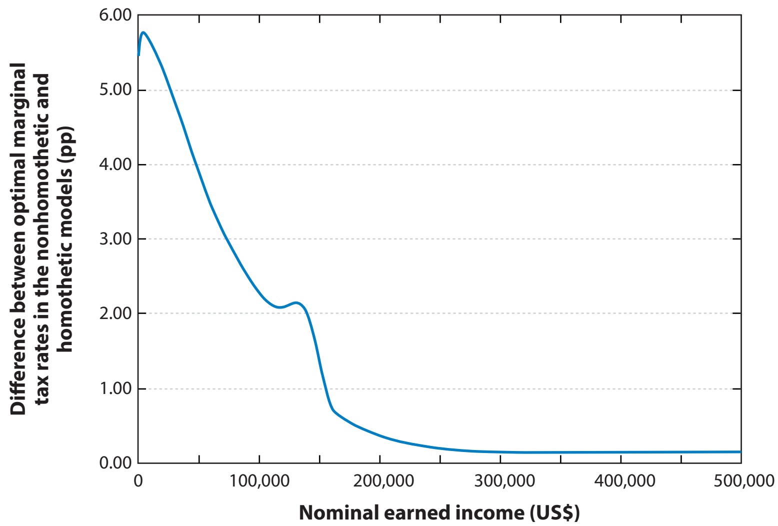

Figure 6

Inflation inequality and optimal income taxation. The figure plots the difference in optimal marginal tax rates across the earned income distribution, comparing the model with non-homotheticities to the baseline model with homotheticities. Both models under comparison feature increasing returns to scale. Abbreviation: pp, percentage point. Figure adapted from Jaravel & Olivi (2020).

to the baseline model with homothetic utility, in the calibrated model with non-homotheticities marginal tax rates increase by over 6 percentage points at the bottom of the income distribution.[27]

Allcott et al. (2019) study the interaction between corrective and redistributive motives. So-called sin taxes on goods such as cigarettes, alcohol, and sugary drinks may fall disproportionately on low-income consumers; therefore, a social planner with strong tastes for redistribution may want to keep them at low levels. Their analysis shows that stronger preferences for redistribution can in fact increase the optimal sin tax under plausible assumptions—for example, if lower-income consumers are more responsive to taxes or are more biased in their consumption choices.

In recent work, Bachas et al. (2020) examine whether consumption taxes can reduce inequality in developing countries. They show that the budget share spent in the informal sector steeply declines with income. The informal sector makes consumption taxes progressive: Households in the top quintile face an effective consumption tax rate that is twice as high as the tax for the bottom quintile. The calibration of a standard optimal tax model shows that, contrary to a widely held view, consumption taxes are redistributive and can lower inequality as much as personal income taxes.

[27]In **Figure 6**, given that the social value of redistribution at the bottom has increased through endogenous price changes, it may seem counterintuitive to see marginal tax rate increases at the bottom of the income distribution. In fact, higher marginal tax rates at the bottom of the income distribution increase the overall amount of redistribution in a more efficient way than increasing marginal tax rates at the top would do. Indeed, high marginal tax rates at the bottom are paid by all agents earning high levels of income without distorting their marginal incentives to work, and all revenue is rebated to the low-income households through the intercept of the tax schedule.

Overall, there is a growing consensus in the quantitative optimal taxation literature that it is important to take into account non-homotheticities and the equilibrium response of prices to changes in redistribution.[28]

5.1.4. Stabilization policy. Recent work also shows that heterogeneity in consumption basket matters for the design of stabilization policies, because spending patterns interact with heterogeneity in price rigidities and marginal propensities to consume across household groups.

Nakamura & Steinsson (2008) and Pasten et al. (2019) show that price rigidities vary substantially across product categories. Clayton et al. (2018) and Cravino et al. (2020) find that more educated and richer households tend to have larger expenditure shares on more rigid sectors. Differential exposure to price rigidity across the income distribution arises in part because richer households spend more on services, which are more rigid than goods; but similar heterogeneity is observed even within services and within manufacturing.

Clayton et al. (2018) study the consequences of this fact for monetary policy using a heterogeneous-agent New Keynesian model. Consider a contractionary monetary policy shock: An increase in the nominal interest rate reduces current aggregate demand and activity and leads to a fall in prices. Price rigidity is a key transmission channel of monetary policy. In this model, college-educated households are more exposed to monetary policy because they buy more from rigid sectors, which leads to two implications.

First, there are distributional effects: The relative price of the flexible sector declines, and therefore real consumption for college-educated households falls more because they buy more from the rigid sector, where prices fall less. Second, there are aggregate effects because of differences in exposure to monetary policy (i.e., to rigidities), which interact with heterogeneity in marginal propensities to consume. In general (see, e.g., Auclert 2019), the aggregate response is magnified (dampened) when monetary policy has a larger direct impact on agents with higher (lower) marginal propensity to consume (MPC). Because of differences in price rigidities, the monetary policy shock reduces consumption more for college-educated households, who have a lower MPC. This leads to a smaller fall in aggregate demand in general equilibrium—that is, this channel dampens the aggregate effect of monetary policy. Similar insights would apply to the study of stabilization policies using fiscal tools. In contrast, the common view emphasizes differences between savers and debtors, implying that household heterogeneity amplifies the effectiveness of monetary policy, because changes in interest rates have a larger direct effect on high-MPC agents.[29]

5.2. Non-homotheticities and Macroeconomic Trends

Stepping back from the analysis of the effects of policies, a rapidly growing literature shows, from a positive perspective, that non-homotheticities help understand long-term macroeconomic trends.

A first series of studies considers long-term changes in sectoral expenditure and employment shares. Boppart (2014) and Comin et al. (2021) show that the long-run decline of manufacturing in developed countries can largely be explained by an income effect: Richer societies spend less on

[28] Without considering optimal policy, Faber & Fally (2020) use a quantitative model to quantify the effects of progressive income taxation and of closing loopholes in corporate taxation on price indices across the income distribution. They find meaningful effects via non-homothetic price indices.

[29] For example, an increase in the nominal interest rate reduces consumption more for debtors, who have a higher MPC; this channel amplifies the intended fall in aggregate demand in equilibrium.

manufacturing, even in the absence of changes in relative prices. A related multi-country analysis by Lewis et al. (2018) shows that ongoing structural change implies declining openness, even in the absence of rising protectionism.

Turning to the long-run change in the labor share, Hubmer (2018) shows that higher-income households spend relatively more on labor-intensive goods and services as a share of their total consumption. Interpreted as stemming from non-homothetic preferences, this fact implies that economic growth increases the labor share through an income effect. He finds that until the early 1980s, this income effect could offset capital-labor substitution. Later on, investment-specific technical change accelerated, leading to increasing substitution of capital for labor, and it began to dominate the income effect. Thus, the stability of the aggregate labor share before 1980s and its decline since then can be explained by a race between non-homotheticities and capital-labor substitution.

Non-homotheticities can also explain the secular decline in interest rates and rising wealth-to-income ratios through the differences in savings rates along the income distribution. Using a model with non-homotheticities in savings calibrated to match micro data on heterogeneity in savings rates, Straub (2018) shows that the rise in permanent labor income inequality since the 1970s can explain a decline in the real interest rate of around 1% and an increase in the wealth-to-GDP ratio of about 30%, as well as a large increase in wealth inequality.[30]

Finally, non-homotheticities can interact with the demand for skilled and unskilled labor. Comin et al. (2020) show that expenditure elasticities are positively correlated with intensities in low- and high-skill occupations across sectors. As income grows, demand shifts toward expenditure-elastic sectors and increases the relative demand for low- and high-skill occupations, leading to labor market polarization. A calibration indicates that this channel can account for a large fraction of the observed rise in the wage and employment shares of low- and high-skill occupations in the United States and in Western Europe. Using international trade data, Caron et al. (2014, 2020) document that skill-intensive sectors are income elastic; trade liberalizations increase average incomes and reallocate demand toward skill-intensive sectors, leading to a demand-driven increase in the skill premium. Related work by Jaimovich et al. (2020) highlights the importance of demand for quality: High-quality goods are more intensive in skilled labor than low-quality goods, and household spending on high-quality goods rises with income.

Shifting focus to demand for factors at a business cycle frequency, Jaimovich et al. (2019) find that consumers trade down in the quality of the goods and purchases they buy during major economic crises like the Great Recession, and that low-quality goods are less labor intensive than high-quality goods. This mechanism increased the severity of the Great Recession: When households traded down, labor demand fell further.

These studies show that non-homotheticities are a powerful force to understand several of the most important macroeconomic changes of the past decades. Using more detailed price and consumption data sets to shed more light on these and other macro trends is an important task for future work.

6. CONCLUSION

This review described the promise of a research program on inflation inequality. Recent evidence suggests that inflation inequality can be first-order, and that taking into account the distributional

[30]Auclert & Rognlie (2017) find that the rise of the top 1% income share since the 1980s could explain a decline in long-run interest rates between 0.45 and 0.85 percentage points.

consequences of price changes is essential in several areas of policy making, from redistributive taxation to trade policy and monetary policy.

Important areas that are ripe for further investigation include advancing the theory of non-homothetic price indices, getting access to granular price and expenditure data for all sectors of the economy, studying drivers of inflation inequality other than trade and technology, accounting for inflation inequality in optimal policy design, and examining how non-homotheticities interact with macro trends.

Much remains to be learned. But one can hope that statistical agencies around the world will soon adopt new data sources and price indices to better measure inflation inequality, and that economists will pay more attention to the distributional effects of prices going forward.

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