Price Shocks are Redistribution Shocks: Systemically Significant Prices for Inequality in the United States

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Abstract

This paper develops a novel empirical framework to identify the sectors that are systemically significant for inequality in the United States. We incorporate decile-specific consumption baskets into an input-output price model to simulate how sectoral price shocks affect income distribution as measured by changes in the Gini coefficient. Using the pre-pandemic sectoral price volatility and the price changes from early 2022 as the price shocks for our simulations, we show that a small set of sectors in energy, food and agriculture, healthcare, chemicals and, to a lesser extent, wholesale trade and housing, have a disproportionate capacity to increase inequality when their prices rise. We find a substantial overlap between the sectors that are systemically significant for inflation and those that are significant for inequality. These findings underscore the limits and costs of conventional monetary policy in addressing supply-driven inflation and point to the need for sector-specific policies for price stabilization.

Keywords: Price shocks; Income inequality; Input–output analysis; Consumption heterogeneity; Supply-driven inflation

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1. Introduction

The recent bout of high inflation in rich countries has been primarily driven by sectoral price shocks (Bank for International Settlements, 2022; Blanchard & Bernanke, 2023; Dao et al., 2024; Weber et al., 2024; Weber & Wasner, 2023). Since households' consumption baskets vary with income, with poorer households spending larger shares of their income on necessities, these price shocks have hit different income groups in heterogeneous ways. Recent studies on the distributional impact of food and energy price spikes have shown that they increase income inequality (Balakrishnan & Parameswaran, 2025; Bettarelli et al., 2023; Claeys et al., 2024; Kröger et al., 2023). The literature studying the relation between sectoral price shocks and inequality has focused on the overall empirical relationship between inflation and income inequality, or on estimating the redistribution that results from a price increase in any one salient sector. But a systemic assessment of which sectors have the greatest potential to trigger increases in inequality when prices spike and are, in that sense, systemically significant for inequality has not been carried out. This paper addresses this gap for the United States.

Identifying systemically significant sectors for inequality is relevant not only from an academic but also from a policy perspective. In a world of overlapping emergencies, climate change, geopolitical tensions and trade wars can unleash renewed rounds of supply shocks that send sectoral prices spiking. There is widespread acknowledgement that such shocks have been the key drivers of recent inflation. However, the default policy response remains interest rate hikes aimed at cooling labor markets (Blanchard & Bernanke, 2023).

Besides the limited effectiveness of monetary tightening in reducing supply-driven inflation, this measure can exacerbate inequality through several channels. Household balance-sheet effects mean that wealthier households—who hold more financial assets—gain from higher returns when interest rates rise, while lower-income and more indebted households face higher debt servicing costs without offsetting asset income (Ampudia et al., 2018; Bunn et al., 2025; Coibion et al., 2017). Labor market effects work in the same direction: contractionary policy suppresses job creation and wage growth most at the bottom of the distribution (Rolim et al., 2024). In supply-driven inflation episodes, heterogeneous-agent and two-agent New Keynesian models further show that tighter fiscal policy erodes real wages, reduces aggregate demand, and raises unemployment, while largely benefiting high-wealth households (Chan et al., 2024; Corsello & Riggi, 2023; Del Negro et al., 2024b, 2024a). Simply put, the standard response to inflation is a policy that leads to further redistribution from the bottom to the top.

Fighting inflation with interest rate hikes rather than targeting the sector from which the price shock emerged is also costly for economic growth and increases the costs for investments needed to enhance supply resilience against future shocks (Dao et al., 2023; Weber et al., 2024; Weber & van't Klooster, 2024). If price spikes in the same sectors are systemically significant for inflation and inequality, supply resilience and stabilization strategies aimed at this set of sectors could contain inflation in a less costly and thus more efficient way while at the same time limiting regressive redistribution.

Following the 2008 financial crisis, the neglect of distributional effects was widely recognized as a serious oversight (Stiglitz, 2015), and landmark contributions by Piketty & Saez (2013), Piketty (2014), Atkinson (2015), and Milanovic (2016), among others, brought rigorous evidence and renewed attention to the issue. The COVID-19 pandemic further underscored the profound social, economic, and health costs of entrenched inequality (Nassif Pires et al., 2020), making the search for inflation-control policies that do not deepen these disparities even more critical.

There is one more reason why such a sectoral approach has the potential to prevent an increase in inequality: price spikes in systemically significant sectors for inflation can coordinate firms to hike prices across the economy in a process known as sellers' inflation, which increases corporate profits and hence results in a functional redistribution of income from labor to capital (Weber et al., 2025; Weber & Wasner, 2023).

In previous work we devised an input-output simulation method to identify systemically significant sectors for inflation (Weber et al., 2024a; Weber et al., 2024b). We find that for the US, eight sectors have by far the greatest potential to trigger inflation when prices spike. These sectors are *Petroleum and coal products*, *Oil and gas extraction*, *Utilities*, *Chemical products*, *Farms, Food and beverage and tobacco products, Housing* and *Wholesale trade*. These are sectors that provide essentials for human livelihoods, essential inputs for production and essential infrastructure for the circulation of goods.

To assess which sectors are systemically significant for inequality, we develop a novel empirical framework that extends our input-output price model. The original model estimates the direct and indirect inflation impact of exogenous price shocks to each sector of the US economy using the cost of the average consumption basket. In contrast, we estimate the impact of these exogenous price shocks on decile-specific consumption baskets and use this information to calculate the effect of these price shocks on income distribution measured by the Gini coefficient. We simulate how a price shock in one sector propagates through the economy via input-output relations, affects the consumption basket of each income group, and ultimately alters the distribution of real income. This produces a ranking of sectors based on their simulated impact on the Gini coefficient, which allows us to find the systemically significant sectors for income inequality.

We apply this method to two sets of price shocks: (1) sectoral price volatility during 2000–2019; and (2) the annual price changes in 2022 Q2, coinciding with the recent inflation surge after the beginning of the war in Ukraine. The first set of price shocks captures long-run price trends, revealing the underlying tendency of certain sectors to be systemically significant for inequality. Using the second set of price shocks, we identify sectors that realized systemic significance in the context of the most recent inflation bout. For each shock, we estimate the change in the Gini coefficient induced by the direct (the initial price shock) and indirect price changes (the price changes induced by the initial shock), rank sectors by their inequality impact, and assess how price instability in certain areas can drive distributional outcomes.

We have three main findings. First, we identify a small set of essential sectors—particularly in energy (e.g., *Petroleum and coal products*), agriculture and food (e.g., *Farms, Food and beverage products*), and healthcare (e.g., *Hospitals, Ambulatory care services*) but also in less obvious sectors like *Chemical products* and to a slightly lesser extent in *Housing* and *Wholesale trade* —as the most critical points of vulnerability that can exacerbate inequality. Second, we find that there is a large overlap between the sectors that are systemically significant for inflation and those that we identify as systemically significant for inequality. Third, we show that one simultaneous shock to all systemically significant sectors in 2022 has a direct effect on inequality equivalent to nearly one year of the average annual Gini increase during the neoliberal era (1980–2021).

Our methodological contribution is a modeling framework to identify systemically significant sectors for inequality and to simulate the distributional consequences of sectoral price shocks using publicly available input-output and consumption data. Empirically, we show that increasing price stability in a few critical sectors helps prevent inflation as well as sudden increases in income inequality caused by price shocks to essentials. From a policy perspective, we challenge the conventional approach to inflation control as the exclusive responsibility of monetary policy and provide a framework to identify sectors that should be the main focus of price stabilization policies.

The structure of the paper is as follows. The second section reviews the literature on inflation heterogeneity and its link to inequality and illustrates how our approach relates to this growing body of literature. In the third section, we present our methodology, including the input-output model, data sources, and assumptions used to simulate the impact of sectoral shocks on the Gini coefficient. Section four discusses our empirical findings. Section five concludes and discusses the implications for policy.

2. Related Literature

Inflation and inequality are connected in several ways. The most direct link is because different income groups have different propensities to consume. Bluntly put, inflation will disproportionately affect groups which consume a greater share of their income, namely lower-income groups. In contrast, consumption has a lower weight for wealthier households, which implies a lower loss in welfare caused by inflation. Taking this difference into account, for instance by using income instead of consumption shares in the construction of price indices for income groups, reveals a stronger effect of inflation on inequality (Schulz & Ipsen, 2025). Our paper ignores this channel by focusing on the consumption baskets of different income groups, which means that all our estimates about the effect of price shocks on income inequality are underestimations of the actual effect.

Inflation is generally measured using the Consumer Price Index (CPI), which aggregates goods and services into broad categories according to the composition of the basket of goods of an average consumer. The CPI can mask the uneven impact of price fluctuations on different households in three key ways. First, because different groups' consumption patterns deviate from the average basket, price changes will impact them differently. The percentage of income spent on each type of goods and services varies according to income levels as well as geographical, demographic, social and cultural factors. Thus, if between-group inflation heterogeneity is driven by different consumption baskets, then the direction of the difference (inflation being pro-poor or pro-rich) will depend on the relative price changes observed in each inflation episode.

Second, since households purchase different specific items with potentially different price changes within the same broad categories, even those with similar spending shares in each category will experience varying inflation levels. Further, even the price of the same item varies across stores and geographical locations, which adds another level of heterogeneity. Third, the choice of the time period for the consumption shares used as weights for constructing the CPI can have important implications for the calculated inflation rate (Jaravel, 2021). For example, Cavallo (2020) shows that the inflation rate calculated using the updated "Covid" inflation baskets is significantly higher than the reported rate for the US and ten other countries, which use the weights from the periods before the inflation surge. He finds that the actual inflation experienced by most households was higher than that recorded using the pre-covid consumption shares since the consumption shares of some economic sectors that experienced higher price surges increased.

Addressing the first bias, i.e. differences in the observed basket composition, requires household microdata, usually taken from household expenditure surveys, which are used to calculate household or group-specific consumption baskets and group-specific consumer price indices. Several studies have estimated the heterogeneity in inflation rates across households in the US and the rest of the world. For the US, studies have documented the importance of group-specific consumption baskets in the measurement of inflation for the period from 1972 to 2022.[1] The seminal work by Michael (1979) found substantial inflation heterogeneity between the households of their sample but not between groups of households, grouped either by income, education, or age. When such between-group heterogeneity existed, it was not persistent over time, suggesting that group-specific CPIs would not diverge substantially from the headline CPI. However, Hagemann (1982) updated their analysis for the period from 1972 to 1982 and found a different result, namely that lower-income and elderly households faced a greater-than-average rate of inflation. Since then, multiple studies have confirmed this result for different time periods and groups: for the period 1987-2000, Hobijin and Lagakos (2005) find evidence in favor of greater inflation rates for the elderly, and that the inflation rate faced by lower-income households is strongly dependent on the (very volatile) price of gasoline, even though they find no evidence of persistence in inflation heterogeneity at the household level. Hobijn et al. (2009) improve the measurement of household inflation and extend the period of analysis for 1984-2004, confirming their previous finding of large household inequality dispersion. They also find a

[1] An exception is Garner et al. (1996), who do not find significant differences between the general and the income-specific inflation rate for the period 1984 to 1994.

negative correlation between the general inflation rate and inflation inequality, implying that, the larger the inflation rate, the lower the between-group difference in inflation. Argente & Lee (2021) show the existence of a particularly high inflation inequality after the 2008 financial crisis until 2013. This is confirmed by Klick and Stockburger (2023) for the whole period from 2006 to 2022.

Similar studies have been conducted for other countries with mixed results. For developed countries, Oldfield and Crawford (2002) find a large and growing dispersion of household inflation rates from the headline average during the period 1976 to 2000 in the UK, with the inflation rate for the poorest decile being slightly lower than for the richest decile. Fessler and Fritzer (2013) and then Fessler et al. (2023) find substantial heterogeneity in inflation rates between groups defined around different dimensions for the periods 2010-2012 and 2020-2022, respectively. These groups include income, education, areas of living (urban or rural), size of municipality, among others. Both document higher exposure to inflation for lower-income households. Menyhert (2023) calculated the difference in inflation rates faced by different EU countries and by income groups within countries in 2022. He shows that there is wide between-country variation (between 6.1% to 25.4%) but also between income groups within each country. In all the countries but the Netherlands, the bottom quintile faced a higher inflation rate than the top. All these differences (between and within countries) are driven primarily by the differences in expenditure shares in food and energy. Colavecchio et al., (2011) confirmed the result that significant inflation asymmetries existed between households among 15 European countries between 1997 and 2008.

Studies that go beyond the simple identification of inflation asymmetries to the estimation of the effect of these asymmetries on the measurement of inequality are most relevant for our purposes. Garcimartín et al. (2021) not only calculate income-specific inflation rates for countries in Central America and the Caribbean, but use them to estimate "inflation-corrected" Gini indexes. These corrected Gini indexes show that the actual decrease in income inequality during the period is only about half of that recorded using unadjusted indices (Garcimartín et al., 2021). Gürer and Weichenrieder (2020) show a similar result for Europe during 2001-2015, namely, that inflation was higher for poorer households, and that ignoring this fact would underestimate the Gini coefficient by almost 0.04. Aprea & Raitano (2025) study the relevance of food consumption share and food inflation in the measurement of inequality for five large EU economies during the period 2020-2023. They calculate and compare alternative measures of inequality: (1) the standard nominal income Gini coefficient, (2) the income Gini coefficient net of food expenditures, (3) the nominal income Gini coefficient net of *inflated* food expenditures and (4) a headline-CPI-inflation-augmented Gini coefficient net of inflated food expenditures. These comparisons allows the authors to study, first, how the measurement of income inequality changes when you only consider income beyond the most basic necessities; how the consideration of food inflation changes the measurement of income inequality, and, finally, the extent to which income indexation to general inflation changes the measurement of inequality in the face of food price increases. Their results show that income inequality is substantially larger when only income beyond food expenditures is considered, that food inflation further increases income inequality, and that income indexation to the headline inflation rate is not enough to keep inequality constant. In other words, their results suggest that changes in relative prices biased against necessities can be an important force driving increasing income inequality.

Finally, both Almås and Kjelsrud (2017) and Goni et al. (2006) show that inflation heterogeneity is an important phenomenon for India (1993-2012) and for Brazil, Colombia, Peru, and Mexico[2] and that, during the periods under consideration, inflation was "pro-poor" or "anti-rich," in contrast to the results of most studies mentioned so far.

Addressing the second bias in measuring inflation, namely the differences in items consumed within categories, or the different prices for the same item, is far more complicated since it requires granular data on household consumption habits. Recent literature has helped study this hitherto underexplored bias in the measurement of inflation. For the US economy, Kaplan and Schulhofer-Wohl (2017) use scanner data to analyze the differences in household inflation rates caused by different consumption bundles and different items purchased within categories. They find that the difference in the inflation rate between the lowest and the top income quartiles is between 6.2 and 9%, most of which is explained by different prices paid for the same categories of goods. This result suggests that the second dimension of inflation measurement is important and that studies that do not account for this fact might under or overestimate the differences in inflation rates between groups. Similar results have been found for other developed countries, such as France and Germany (Kiss & Strasser, 2024) and Austria (Messner & Rumler, 2024).

[2] Country-specific periods between 1984 and 2003.

The studies reviewed so far have focused exclusively on the quantitative relationship between inflation and inequality, ignoring the question of what conditions make a positive correlation between inflation and inequality more likely. The recent inflation episode, however, has brought attention to the role of price shocks in explaining both inflation and its consequences. Claeys and Jeanrenaud (2024), for example, emphasize the role of rising energy prices in the "anti-poor" inflation episode that Europe has faced in recent years. The role of price shocks in energy sectors and their socioeconomic consequences have been studied extensively using modern empirical methods. Bettarelli et al. (2023) show that, for 129 economies during the period 1970-2013, energy inflation is associated with an increase in the Gini coefficient, with the effect being larger for developing countries. Kröger et al. (2023) show how the recent natural gas price spike in Germany disproportionately affected poorer households as they spend a substantially higher share of their income on gas than wealthier households. Similarly, Balakrishnan and Parameswaran (2025) test the structuralist thesis that in developing economies, the price of agricultural goods is the main driver of inflation. Using data for India during the period 1996 to 2023, they find that the changes in the relative price of agriculture are the primary determinant of inflation.

In sum, there is overwhelming evidence about differences between household-specific inflation rates and the headline average rate. This difference is caused by heterogeneous consumption patterns across households and groups and by differences in the prices of the same items paid by different households. There is also growing evidence of the inflationary and worsening effects on inequality of energy price shocks.

Inflation in different periods can have different origins. It can be demand-pull or cost-push inflation. Although changes in relative prices can be a part of the inflationary process in either case, it is certainly a defining feature of cost-push inflation. This cost push can come from different sectors, and the relative power of labor and capital determines who ends up carrying the cost. Due to this heterogeneity across different dimensions, it should be no surprise that studies using data for different periods and geographies come to different conclusions. Nevertheless, there is ample evidence that the latest inflation bout in the US and Europe has been a sellers' inflation in which capital was more successful in protecting profits than labor in protecting real wages (Arce et al., 2023; Bivens, 2022; Hansen et al., 2023; Uxó et al., 2025; Weber et al., 2025; Weber & Wasner, 2023). Similarly, studies on the most recent inflation episode find inequality- or poverty-increasing effects of energy and food inflation

(Claeys & Jeanrenaud, 2024; Kröger et al., 2023; Balakrishnan & Parameswaran, 2025). Our paper pursues a novel approach. Assuming cost-push inflation and relative strength of capital compared to labor as evidenced in recent years, we aim to identify what sectors matter most for inequality when hit by price shocks.

Other studies have picked energy and food in an ad hoc fashion due to the large price changes and high and heterogenous weights in consumption baskets. We develop a framework to identify a set of sectors that represent points of vulnerability for inequality when hit by price shocks. In other words, we aim to find the sectors that are systemically significant for inequality in the United States economy. In contrast to Schulz and Ipsen (2024) -who found the most relevant sectors for income quintiles in Europe during the period 2000-2014- we achieve this by estimating the effect of price shocks on income inequality as measured by the Gini coefficient. In this way, we not only obtain a classification and ranking of sectors that are inequality-increasing and inequality-reducing, but also estimates of approximately how different kinds of shocks can affect income inequality in the US economy. We then compare those estimates with the observed evolution in income inequality during the last 40 years to have a better perspective of the potential of price shocks to trigger not only inflation, but also growing inequality in the US economy.

3. Methods and Data

3.1 Methods

This paper uses and extends the method first proposed by Weber et al. (2024) to identify systemically significant prices for inflation. The basis is the Leontief price model, an input-output representation of an economy's sectoral composition of prices. The central equation of the model is equation (1):

$$P = (I - A')^{-1}(v + m) = L'(v + m) \tag{1}$$

Assuming there are n sectors in this economy, the explanation of each of the terms in equation (1) is the following:

- P is the $n \times 1$ vector of prices.

- A is the $n \times n$ matrix of domestic direct requirements, with element a_{ij} representing the direct (dollar) amount of the output of sector i necessary to produce a dollar unit of output in industry j.
- v is the $n \times 1$ vector of unit-value-added. Element v_i is the share of value added in gross output for sector i.
- m is the $n \times 1$ vector of unit-imports. Element m_i is the share of input imports in gross output for sector i.
- $(I - A^{'})^{-1} = L'$ is the transpose of the Leontief domestic total requirements matrix. Element L_{ij} represents the *total* (direct and indirect) dollar amount of the output of sector i necessary to produce a dollar worth of the output of industry j.

Equation (1) shows what share of each price can be attributed to each sector of the domestic economy (captured by $L'v$) and what share corresponds to production generated outside the domestic economy (captured by $L'm$). This allows us to study how a change in the price of one sector's output can affect the prices of the rest. In equation (1), such changes can only come from the vectors of unit-value added (wages or profits) and unit-imports. To study the more general case of an exogenous price increase in a sector, equation (1) can be modified in the following way:

$$\Delta P_E = (I - A'_{EE})^{-1} A'_{XE} \Delta P_X \tag{2}$$

All the terms in equation (2) are partitions of the original terms in equation (1). Here, E represents the subset of endogenous, and X the subset of exogenous sectors. In this setting, endogenous means that the price of that sector is determined within the system, following a cost-plus-markup pricing rule, whereas exogenous means that they are taken as given and hence unaffected by the price of other sectors (as in the case of commodities that follow international prices). The assumption of a cost-plus-markup pricing rule for endogenous sectors is consistent with the dynamic of *markup protection* after cost shocks, which has been widely documented during the last inflation episode (Weber et al., 2025). The subindexes in equation (2) represent which sectors have been kept in the rows and columns of each vector or matrix. Thus, equation (2) shows how the prices of all endogenous sectors change (ΔP_E) when there is a price shock ΔP_X, which can come from a single sector or many simultaneously.

The extension we present in this paper consists of calculating income-decile specific inflation rates associated with each price shock ΔP_X[3]. We achieve this by obtaining a weighted average of the vectors (ΔP_E and ΔP_X) as represented by the equation below:

$$IP^K(\Delta P_X) = c_X^K \Delta P_X + \sum_{i \notin X} c_i^K \Delta P_{Ei} = IP_{dir}^K + IP_{ind}^K \tag{3}$$

Here, $IP^K(\Delta P_X)$ represents the total inflation impact faced by decile K caused by a shock $\Delta P_X c_j^K$ is the share of sector j in decile's K personal consumption, and ΔP_{Ej} is the jth element of vector ΔP_E. The first term of the sum is the direct inflation impact, IP_{dir}^K, which captures the part of the total increase in the price of the consumption basket of decile K that was caused just by the price shock, whereas the second one is the indirect inflation impact, IP_{ind}^K, capturing the part of the inflation rate for decile K caused by the impact of the price shock ΔP_X on the prices of endogenous sectors.

This implies that every price shock ΔP_X is associated with an inflation impact for each decile in the income distribution of the US economy. But to know what sectors are *inequality-increasing* and the extent to which they are, we need to find a new aggregate measure associated with these different decile inflation impacts. We achieve this by simulating the effect of these inflation rates on the Gini coefficient of income distribution. To implement this, we make the following crucial assumption: that the percent change in the income of every individual in decile K will be given by the decile-specific inflation impact, IP^K.[4]

Formally, the new income of individual i, who belongs to decile K, will be given by:

$$I_1^{iK}(\Delta P_X) = \frac{I_0^{iK}}{1 + IP^K(\Delta P_X)} \tag{4}$$

Where I_1^{iK} is the income of individual i in time period one, after the price shock ΔP_X, and I_0^{iK} is the original income of individual i, before the price shock. Let I_0 represent the initial overall income

[3] For our analysis, we also group deciles into three broader groups: the *bottom* (deciles one to five), the *middle* (deciles six to nine) and the *top* (decile ten). The exact same analysis described for the case of deciles applies when considering only these three broader groups.

[4] It is important to note some consequences of this assumption. In the case of an increase of inequality, this assumption underestimates this increase. This happens because the bottom deciles spend a larger share of their income in consumption compared to the higher deciles. For the same reason, we tend to overestimate inequality reductions.

distribution, and $I_1(\Delta P_X)$ the new income distribution associated with price shock ΔP_X. Then we obtain the main metric of this paper as shown in equation (5) below:

$$\Delta G(\Delta P_X) = G\big(I_1(\Delta P_X)\big) - G(I_0) \tag{5}$$

Thus, $\Delta G(\Delta P_X)$ is the change in the Gini coefficient associated with a price shock ΔP_X, and is equal to the difference between the original Gini coefficient and the new Gini coefficient associated with the post-shock income distribution. In all simulations, we rank each industry in descending order according to their impact on the Gini coefficient, and this allows us to identify the sectors whose prices are systemically significant for inequality.

We also perform simulations in which more than one industry receives the shock. Thus, the vector ΔP_X contains more than one element that is different from zero. In particular, we simulate a joint shock to the sectors that we identify in our results as systemically significant for inequality. Importantly, for these simulations of joint shocks, *we only consider the direct inflation impact of the joint shock*. This is the case because, as we assume more industries to be exogenous, the feedback effects through input-output linkages between exogenous sectors disappear. Focusing on the direct inflation impact also provides a simpler interpretation: it shows the inequality impact of the observed joint price increases to significant sectors in the US economy. To accommodate this change, we only need to substitute IP^K_{dir} for IP^K in equation (4).

The price shocks that we use in our simulations are:

I. Sectoral price volatility 2000-2019

II. Annual price change between 2021 Q2 and 2022 Q2.

The first magnitude measures the tendency of prices to move for different sectors before the COVID-19 pandemic and the beginning of the last inflation episode. The simulation using these price changes allows us to identify sectors that are potentially significant for inequality, which we denominate as *latent*. The second price change corresponds to the price shocks followed by the beginning of the war in Ukraine in February 2022.

3.2 Data

We use the US input-output tables at the summary level after redefinitions provided by the Bureau of Economic Analysis (BEA) for 2019 to estimate the indirect effect of price shocks, as represented in equations (1) and (2). We obtain data on price changes from the chain-type gross output price index series provided by the BEA. This data allows us to identify the observed price changes between 2000-2019 and 2021 Q2 and 2022 Q2, which correspond to ΔP_X .

The consumption shares by input-output sectors and deciles, which correspond to c_K^i, come from the Distribution of Personal Consumption Expenditures (PCE) provided by the Bureau of Labor Statistics (BLS). However, this data uses the NIPA sectoral categorization. We use the PCE bridge data supplied by the BEA to convert these NIPA categories into the NAICS categories in which the input-output data is organized. The details of the conversion are explained in Appendix B. For our simulations, we use the consumption shares for the year 2019 whenever the price shock is the sectoral price volatility between 2000 and 2019. When the price shock is the annual price change from 2021 to 2022, we use the consumption shares for the year 2021.

Finally, the data on household income to calculate the original Gini, the new income distribution after the price shock and the associated new Gini coefficient, comes from the Consumer Expenditure Survey (CE) provided by the BLS, for the year 2020. This data corresponds to I_0^K in equation (4).

4. Results

This section presents the results of our simulations, which allow us to identify the systemically significant sectors (SSS) for inequality in the United States and to estimate their potential effect on the income Gini coefficient[5]. In our simulations, each price shock generates a new structure of relative prices, with each price being greater or equal than before the shock. Since, by assumption, all households face the same prices, but their consumption baskets differ, each income group will see their real income affected to different extents. This results in a new distribution of income, which allows us to calculate the change in the Gini coefficient associated with each individual price shock.

[5] Table A1 in Appendix A shows the summary of all the results presented in this section.

In our research method, the difference in personal consumption expenditure shares across income groups is the element driving changes in income inequality. To illustrate the methodological importance of consumption heterogeneity, in Figure 1 we report the different consumption shares in 2019 for three broad income groups: the *bottom* (deciles one to five), the *middle* (deciles six to nine), and the *top* (decile ten). Sectors are arranged in descending order of importance in reference to the *bottom* group. Two main results emerge immediately: first, the largest share of household consumption expenditures goes to a small group of sectors, and, secondly, for almost every sector, there is a large variation in the consumption shares across the three income groups. The *bottom* tends to have larger expenditure shares compared to *middle* and *high* for the sectors that most households spend the larger share on. This relationship tends to reverse for sectors that receive smaller expenditure shares across income groups. The first result, namely, the disproportionate importance of some sectors in households' consumption, is sufficient to study the sectors that are systemically important for overall inflation, as in Weber et al. (2024). The second one, the income-specific variation, is the basis for analyzing the systemic significance of prices for income inequality.

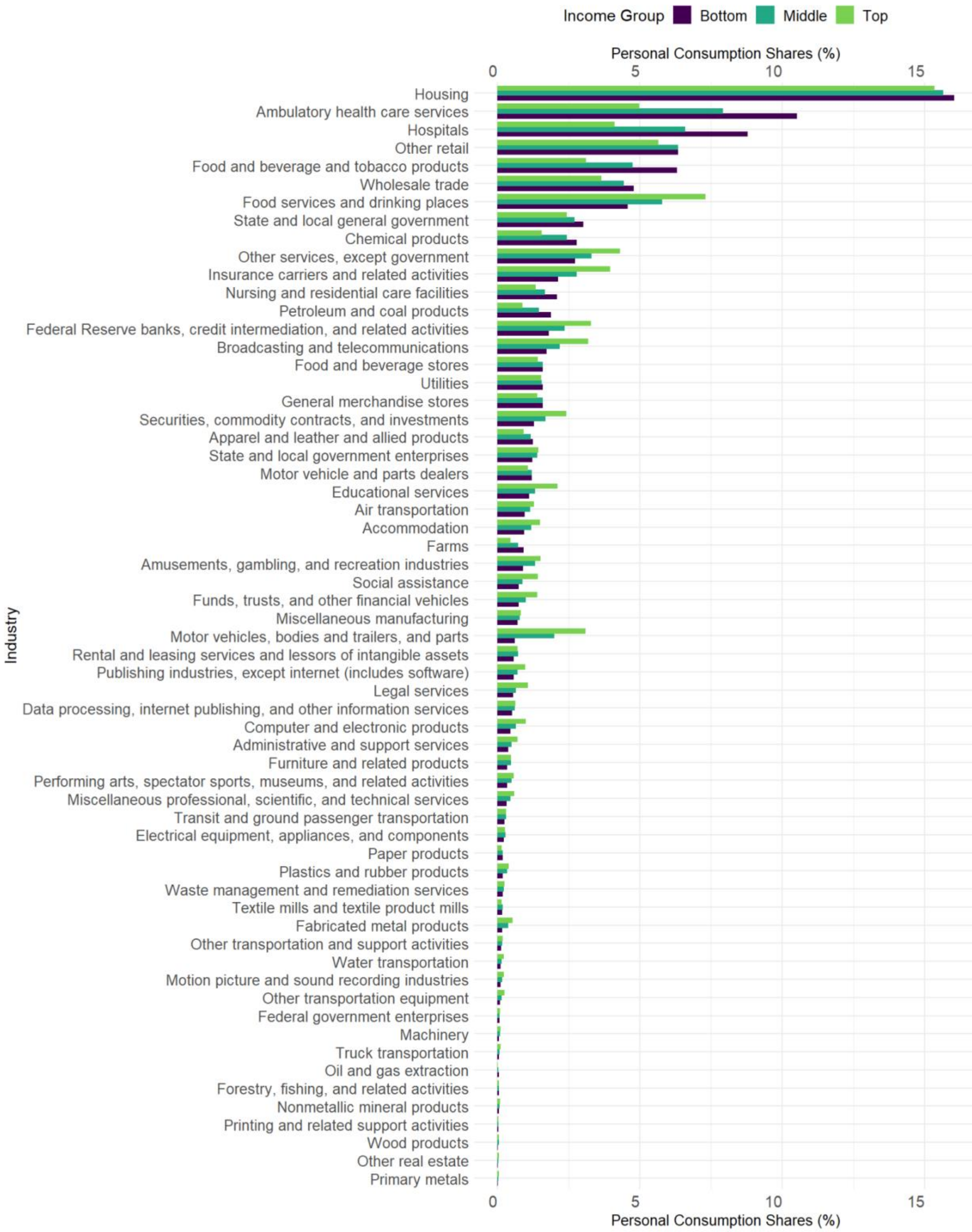

Figure 1. Consumption shares by income group. The Figure shows the 2019 Personal Consumption Expenditure Shares of each sector for three income groups: the *bottom* (deciles one to five), the Middle (deciles six to nine), and the *top* (decile ten). *Sources:* BEA input-output accounts, BEA Personal Consumption Expenditure bridge, BLS Distribution of Personal Consumption Expenditures.

4.1 Pathways to systemic significance for inequality

There are two main ways this consumption heterogeneity translates into changes in income inequality. The first is the *direct* channel, which is straightforward: if there is a price shock for a sector that is more important for the consumption of the poor than the rich, then the shock will be directly inequality-increasing. For example, in *Ambulatory healthcare care services* the share in personal consumption for the *bottom* is more than twice as large as for the *top*. Assuming that consumption shares remain constant, as we do in all our analyses, a shock would increase the cost of the whole consumption basket for the *bottom* by around 1.05%, but only around 0.50% for the *top*.

Second, the *indirect* channel to increase income inequality depends on the specific forward linkages of the sector that receives the shock, and hence on the prices in downstream sectors that would increase the most after the shock. Here the input-output modelling becomes relevant. To illustrate this channel, let us assume two scenarios: in the first one, *Farms* exclusively provide inputs to *Food services and drinking places;* in the second one, exclusively to *Food and beverage and tobacco products* – two sectors that vary in their importance to different income groups. Since *Food services and drinking places* is more important for the *top* (7.3% consumption share) than for the *bottom* (4.6% consumption share), a price shock to *Farms* in the first scenario would be indirectly inequality-decreasing. In contrast, because a greater consumption share of the *bottom* (6.3%) than of the *top* (3.2%) goes to *Food and beverage and tobacco products,* a price shock to *Farms* in the second scenario would be inequality-increasing. In the actual data, most goods function as inputs (directly or indirectly) for all other goods to some degree. Still, the relative importance of each input varies, which will make a price shock to a particular sector to be indirectly inequality-decreasing or increasing.

These specifications allow us to define what we call the *pathways to systemic significance for inequality*. That is, the potential of a sector to increase income inequality depends positively on:

(1) The extent to which it is more important for the personal consumption of the poor than for the rich (direct channel).
(2) The extent to which it is used more intensively as an input by goods that are relatively more important for the consumption of the poor than for the rich (indirect channel).
(3) The magnitude of its price change, which in turn affects the magnitude of the inflation impact for each income group.

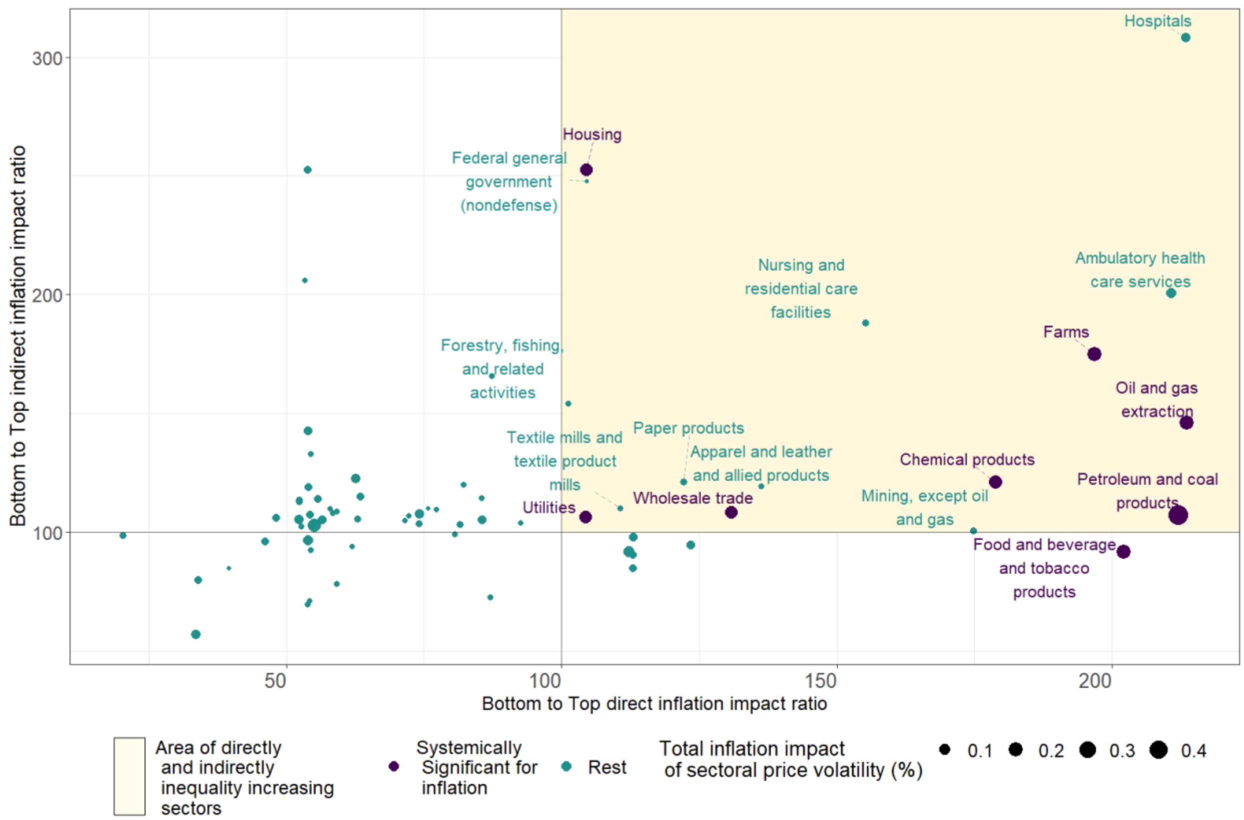

Figure 2. Pathways to systemic significance. The figure represents the pathways to systemic significance for inequality. It shows the *bottom* to *top* direct and indirect inflation impact ratios for the 71 sectors of the US 2019 input-output table, using the sectoral price volatility from 2000 to 2019 as the exogenous price increase for each sector. The size of the dot represents the magnitude of the total inflation impact associated with the price shock. The horizontal and vertical lines represent the 100% threshold for the direct and indirect *bottom* to *top* ratios. The direct ratio measures the extent to which a good is more important for the consumption basket of the *bottom* than for the *top*. The indirect ratio measures the extent to which the price shock to a sector affects the prices of other sectors that are more important for the *bottom* than for the *top*. Thus, when the direct (indirect) ratio is larger than 100%, we say that the sector is directly (indirectly) inequality-increasing. Sectors in the colored northeast quadrant of the figure are both directly and indirectly inequality-increasing. Systemically significant sectors for inflation are highlighted. Sources: BEA input-output accounts, BEA Personal Consumption Expenditure bridge, BEA chain-type price indexes for gross output by industry, BLS Distribution of Personal Consumption Expenditures.

We represent these three pathways for our 71 industries in Figure 2. We use the sectoral price volatility (defined as the standard deviation of sectoral annual price changes) during the period 2000 – 2019 to define the magnitude of the price change. This captures the general tendency of sectoral prices to move. The horizontal axis shows the direct *bottom* to *top* inflation impact ratio, which is simply a measure of the weight in the consumption share for the two groups. This measure calculates the inflation impact for the *bottom* and the *top* income groups. For example, *Hospitals*, *Ambulatory health care services*, and *Petroleum and coal products* are sectors on which the *bottom* spends much larger shares of their personal consumption than the top and that have hence high direct *bottom* to *top* income ratios. The vertical axis shows the indirect *bottom* to *top* inflation impact ratio. It is a ratio of the increase in the cost of the whole consumption basket for the *bottom* and the one for the *top*, *excluding* the price increase of the shocked industry (that is why it is only the indirect channel). For instance, *Farms* has an indirect *bottom* to *top* ratio of 175, meaning it is used as an input for goods that are more important for the consumption of the *bottom* than for the *top* (for example to produce food).

The horizontal and vertical lines represent the 100% direct and indirect inflation impact ratios – on those lines a price shock is inequality-neutral in respect to the direct or indirect inflation impact. For example, the expenditure share on *Utilities* is similar across the three income groups and that sector is hence close to the vertical line. Sectors to the right (above) of the horizontal (vertical) line can be interpreted as directly (indirectly) inequality-increasing. This North-East quadrant is highlighted for an easier identification of sectors that are both directly and indirectly inequality-increasing. Finally, the size of the dot represents the total inflation impact associated with the sectoral price volatility during the period 2000-2019 for the average consumption basket. It is important to be aware that, since the values in the axes are ratios, they don't tell anything about the actual magnitude of the inflation impact. This is why this third pathway -the magnitude of the effect- matters: it helps distinguish relevant sectors for inflation and inequality from those that are not, despite their high direct and indirect *bottom* to *top* ratios. For example, a price increase in *Paper products* is both directly and indirectly inequality increasing, but due to the low forward linkages or weights in consumption baskets it is not an important sector for inequality – as our subsequent analysis reveals. Conversely, a price increase in *Food and beverage and tobacco products* has a large direct inequality-increasing effect and a slightly decreasing indirect effect but is important for inequality also because of the high weight in consumption shares.

In Figure 2, we highlight the eight sectors identified as systemically significant for inflation by Weber et al. (2024). This allows us to see the extent to which the sectors with the greatest potential to trigger inflation can also increase income inequality when subject to price shocks. The first salient result from Figure 2 is that most of the sectors identified as systemically significant for inflation are also directly and indirectly inequality-increasing, as can be seen from the fact that all purple dots but *Food and beverage and tobacco products* lie on the North-East quadrant[6].

[6] Very importantly, the fact that a sector, such as *Food and beverage and tobacco products*, does not lie on the North-East quadrant, does not imply that it will not be overall inequality-increasing. One of the dimensions might be important enough to offset the other ones.

The direct channel is the most important one: the *bottom* to *top* direct inflation impact ratio for the directly inequality-increasing sectors ranges from 178% for *Chemical products* to 213% for *Oil and gas extraction*, meaning that changes to the prices of those sectors will impact the purchasing power of the income of the *bottom* twice as hard as that of the *top*. *Farms, Food and beverage and tobacco products, and Petroleum and gas extraction* lie between these ratios. Furthermore, the indirect ratio is larger than the average for *Farms* and for *Oil and Gas extraction* (175% and 146%, respectively). Price spikes in these sectors impact more significantly the prices of goods that are relatively more important for the poor than for the rich.

On the other end of the spectrum, the inequality-increasing potential of *Utilities* and *Wholesale Trade* is smaller, as the indirect ratio is close to 100 and the direct ratio is not very large. *Housing* also belongs to this group, but it deserves special consideration. It is by far the most important sector in terms of consumption expenditures for all groups (more than 15%, see Figure 3), yet the direct ratio is very small, and, despite the large indirect ratio, its forward linkages are negligible. Nevertheless, a caveat is necessary regarding the direct ratio: the apparent symmetry in consumption shares between income groups arises from the way the Bureau of Economic Analysis calculates Personal Consumption Expenditures for *Housing*. These include both the actual rent paid by tenants and the imputed rent for owner-occupiers, meaning what they would have paid if they rented their home[7] (Mayerhauser & Reinsdorf, 2007). As a result, even wealthy households who own their homes outright are treated as if they were paying rent to themselves. Instead of showing very low housing costs (because they do not pay rent), the accounts impute a cost of housing services based on comparable market rents. Accordingly, an increase in the output price of *Housing* means that the cost of consuming housing services (shelter) has gone up for all households, regardless of tenure. For tenants, this reflects higher actual rents; for owners, it reflects higher imputed rents—what they would have to pay if they rented a comparable property, even though they are not actually facing such increases. To capture the true effect of housing prices on income inequality, one would need a different treatment of the sector—one that distinguishes between actual cash outlays of tenants and owners, rather than imputing the same type of expenditure across all households.

[7] The rationale behind the imputation of rent costs for owner-occupiers is that it "is necessary in order for GDP to be invariant when housing units shift between tenant occupancy and owner occupancy" (Mayerhauser & Reinsdorf, 2007:1)

There are two additional sectors that emerge as potentially significant for inequality which are not significant for inflation: *Ambulatory health care services* and *Hospitals*. They are particularly important because of the very large direct *bottom* to *top* ratio, given that the consumption shares for the *bottom* are very high (around 10.5 and 8.8%, respectively). Although the indirect ratio is also high, they share with *Housing* the feature of being almost completely unimportant as inputs for other sectors, so the indirect effect is negligible. The significance for these sectors can be confirmed by looking at the total inflation impact associated with their sectoral price volatility, which is equal to 0.05% for *Hospital* and 0.07% for *Ambulatory healthcare services*. This contrasts with the other sectors in the North-East quadrant that are not systemically significant for inflation, in the sense that their inflation impact is generally low and hence also their potential to increase income inequality.

4.2 Income specific inflation heterogeneity

In this subsection we analyze the inflation heterogeneity associated with the actual price shocks observed in 2022 Q2 measured as the annual sectoral price change in the context of the Ukraine war inflation. The gray bar in Figure 3 represents the average total inflation impact of the sectoral price shock, whereas the three dots represent the specific inflation impact for the three income groups. The main result obtained from the figure is that, for the top ten sectors in terms of total inflation impact, the inflation impact faced by the *bottom* is larger than for the middle and the *top*. The only exception is *Food services and drinking places*. Furthermore, except for *Housing*[8] and *Utilities*, the gap in inflation impact between *bottom* and *top* is substantial, ranging from 0.14 percentage points for *Chemical products* to 0.52 percentage points for *Petroleum and coal products*. In other words, the bottom experienced a total inflation impact that was 0.14 to 0.52 percentage points higher than that of the top for those ten sectors.

[8] The reason for this apparent symmetry is explained in the previous subsection.

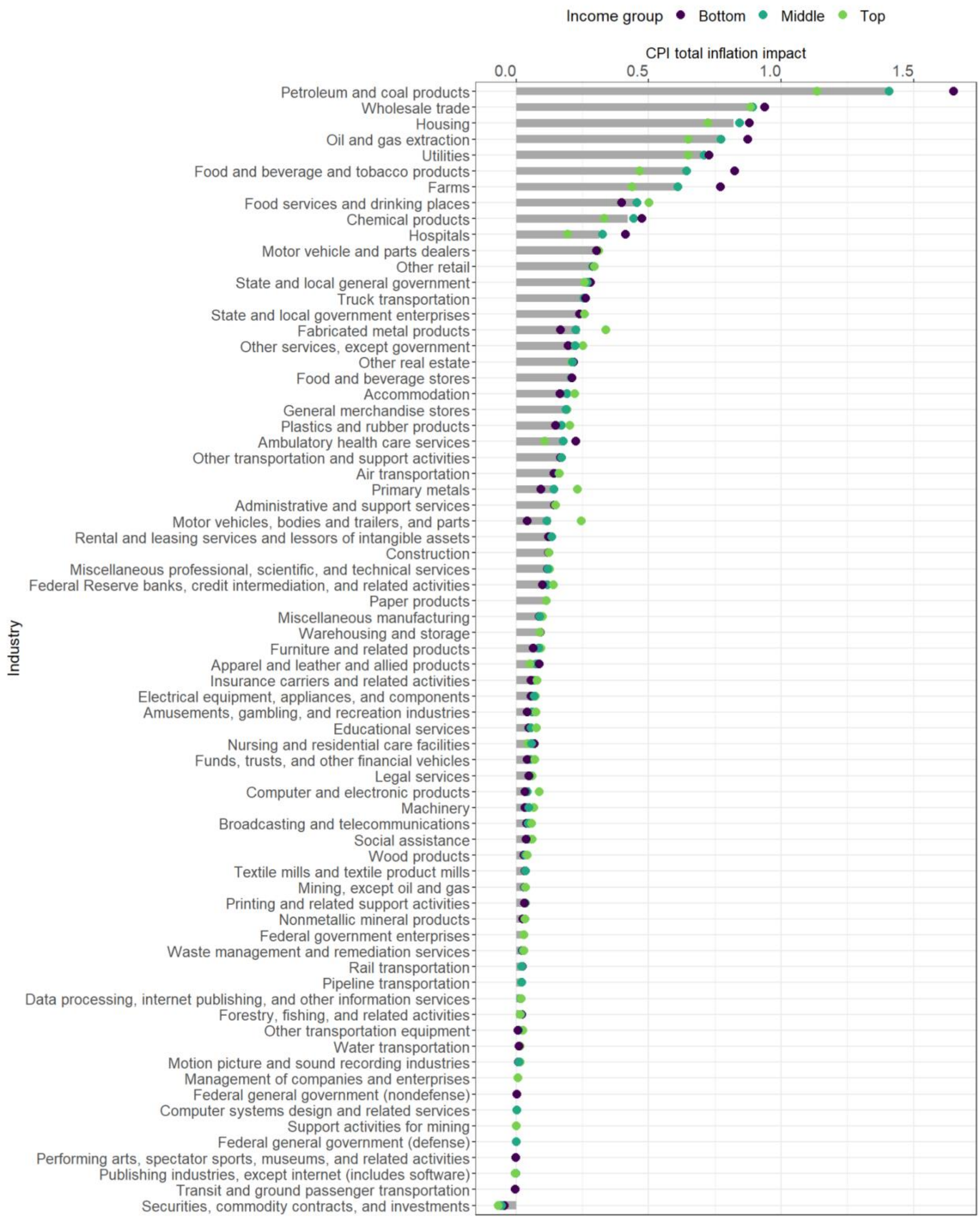

Figure 3. Inflation impact by major income groups. The figure reports the simulated inflation impact of the observed annual price change in 2022 Q2 of each sector. The length of the bar represents the average inflation impact, whereas the three dots represent the inflation impact by income group: the *bottom* (deciles one to five), the Middle (deciles six to nine), and the *top* (decile ten). Sources: BEA input-output accounts, BEA Personal Consumption Expenditure bridge, BEA chain-type price indexes for gross output by industry, BLS Distribution of Personal Consumption Expenditures.

Moreover, aggregating deciles into three broad categories can mask the actual size of the heterogeneity. In Figure 4, we report the direct and indirect inflation impact by decile for the eight systemically significant sectors for inflation and the two healthcare sectors given their large direct inflation impact ratio and high average weight in the consumption basket. The most visible result is that for the eight systemically significant sectors for inflation the consumption share is declining with income. In other words, the poorer the household, the more important those goods are for its personal consumption and hence the larger inflation impact. This result also holds in a slightly weaker form for the two healthcare sectors and the *Utilities* sector. For *Utilities*, the third to the eighth decile dedicate similar shares of their consumption; the bottom two deciles a larger share, and the top two deciles a smaller share. In healthcare, the poorest decile spends less than the next decile but otherwise the inflation impact falls with income. *Chemical products* and *Wholesale trade* – both sectors with large indirect inflation impacts – are the only clear exceptions to the general pattern. Overall, the figure shows that the gap in inflation impact between income deciles is larger than that suggested by the gap between the *bottom* and the *top*.

The disparity in inflation impacts between income groups follows a well-defined order. The gap is the largest in the food-agriculture sectors, (*Farms* and *Food and beverage and tobacco products*), followed by the two healthcare sectors (*Hospitals* and *Ambulatory healthcare services*), and then by the energy sectors (*Oil and gas extraction* and *Petroleum and coal products*). For all the groups, the difference is substantial. For instance, the average inflation impact for *Food* is 0.65%. However, for the poorest 10% of the population, the impact reaches 1.06%, which is around 65% higher than the overall average and 126.9% greater than the impact experienced by the wealthiest 10% (who face an inflation impact of 0.47%). These numbers are very close to those observed for *Farms*.

Within the energy sectors, the gap is the largest for *Petroleum and coal products*: the bottom decile faces an inflation impact of 1.76%, which is 25.31% higher than the average of 1.4% and 54.86% greater than the impact faced by the top decile (1.14%). For *Oil and gas extraction*, the inflation impact for decile one is 0.93%, which is 20.64% greater than the average (0.77%) and 42.74% greater than the inflation impact for the top decile (0.65%).

These disparities illustrate the uneven burden of inflation triggered by specific price shocks across income groups, with lower-income households bearing a disproportionate share of the impact, particularly in the most essential sectors: Food, healthcare, and energy.

Finally, the figure allows us to inspect the role of the indirect inflation impact in amplifying or dampening the gap between the poorest and the richest deciles. Visual inspection suggests that the indirect effect is declining in income for *Farms* and *Oil and gas extraction*; in other words, the inflation impact gap between poor and rich households are amplified in these sectors as the price shock propagates via forward linkages. For the remaining sectors with a positive indirect effect, it is virtually constant across deciles, meaning that it has a neutral effect on income inequality.

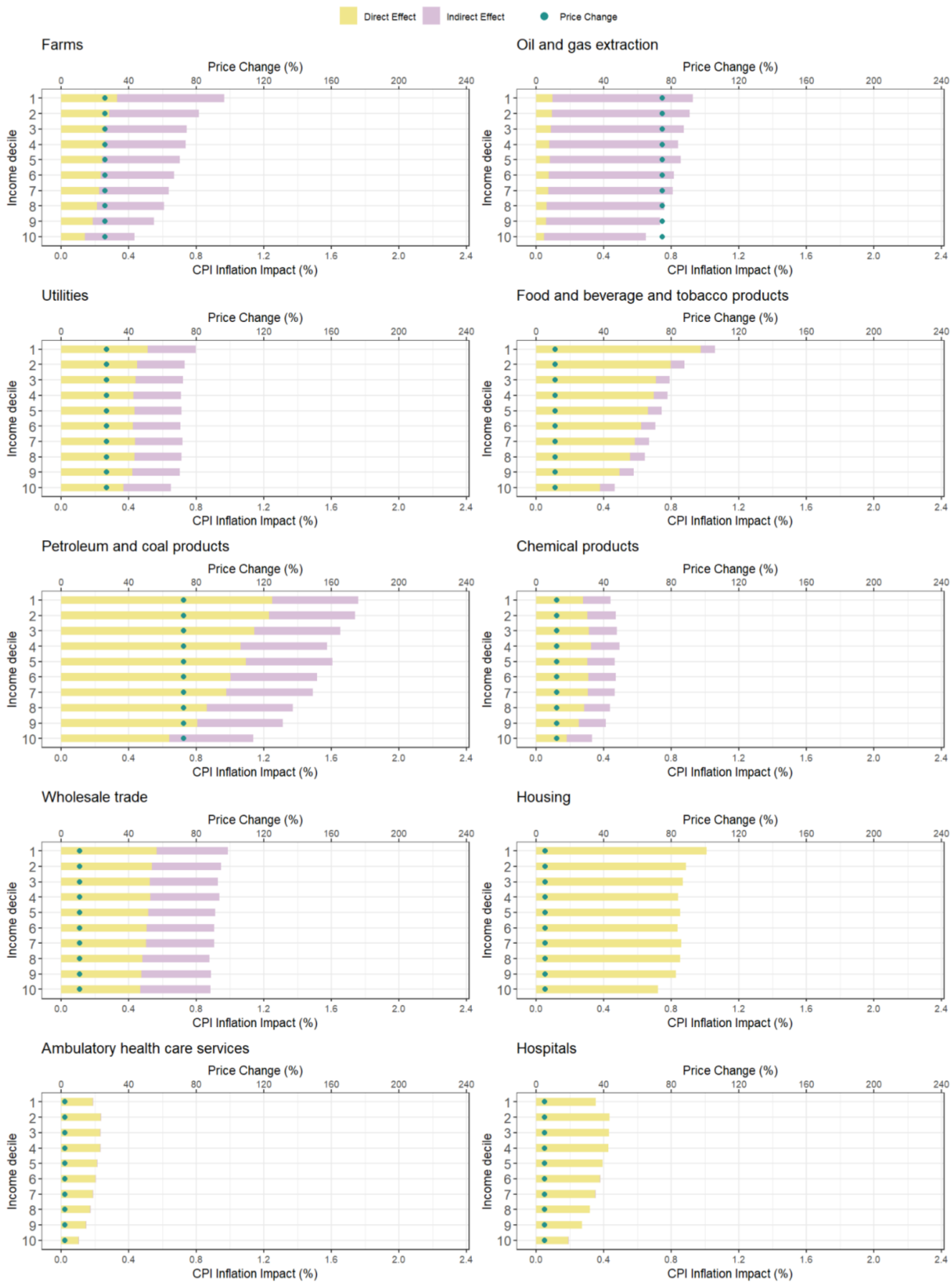

Figure 4. Inflation impact by decile for systemically significant sectors Each panel shows the inflation impact on a synthetic CPI for each income decile of a shock to a particular sector. The combined length of the yellow and purple bars represents the total inflation impact, and the green dot the observed 2021 Q2 - 2022 Q2 annual price change. Sources: BEA input-output accounts, BEA Personal Consumption Expenditure bridge, BEA chain-type price indexes for gross output by industry, BLS Distribution of Personal Consumption Expenditures.

4.3 Systemically significant sectors for inequality

Figure 6 synthesizes all the results obtained so far and allows us to define the sectors that are latently significant for inequality. It ranks all sectors based on the change in the Gini that results from sectoral price changes. The Figure shows the price change that enters the simulation (yellow dot), the associated total inflation impact (purple bar), and the total impact on the Gini. This helps compare the effect of the price shock on both inflation and income inequality. We use the sectoral price volatility during the period 2000-2019 to identify the sectors that are latently systemically significant for inequality. In other words, this exercise ranks those sectors that had the greatest potential to unleash inequality before the COVID-19 pandemic. These results are dependent on the pathways explained above: the total effect of a price shock to a sector on the Gini coefficient will depend on the extent to which this sector is directly or indirectly inequality-increasing, and the total inflation impact associated with that shock.

The results are consistent with the preceding analysis. First, the potential to substantially increase income inequality is concentrated in fewer sectors and to a greater extent than the potential to trigger inflation. The industries in the top eight, ranked by their impact on the Gini coefficient, are *Petroleum and coal products, Farms*, *Food and beverage and tobacco products*, *Chemical products*, *Oil and gas extraction*, *Ambulatory health care services*, *Hospitals* and *Wholesale trade*. We define these sectors as latently significant for inequality. This result confirms our intuition that there is a large coincidence between the systemically significant sectors for inflation and inequality. The only two exceptions are *Housing* and *Utilities*, given the characteristics we described before. In other words, those sectors that exhibited large price volatility in the first two decades of the century, and that have the potential to contribute most to inflation, also have the greatest potential to contribute to inequality. If this finding also holds for realized systemic significance, it has important implications for policy. It implies that measures that prevent price shocks in these sectors are both effective in containing inflation risks and inequality shocks.

4.4 Inequality effects of sectoral price shocks

Ultimately, we want to assess whether the latently significant sectors for inflation were also the sectors with realized systemic significance when the 2022 price shocks hit and whether the increase in inequality from these sectoral price shocks has a significant magnitude. To this end, we first simulate the effect on the Gini coefficient of the observed price shocks in 2022 Q2 measured in terms of annual price changes. The results are displayed in Figure 7. Fourteen sectors have a positive effect on income inequality; however, the largest effects are concentrated in the top eight. Seven out of these eight sectors are latently significant for inequality; the only exception is *Wholesale Trade*, which ranks in number ten. *Housing,* in turn, ranks number seven, given its relatively large price increase and outstanding share in the average consumption basket. In other words, *Housing* proved to be a relevant sector for income inequality in 2022, despite the way in which the accounting framework of consumption expenditures obscures, to some extent, the disparity in housing expenditures between poor and rich households.

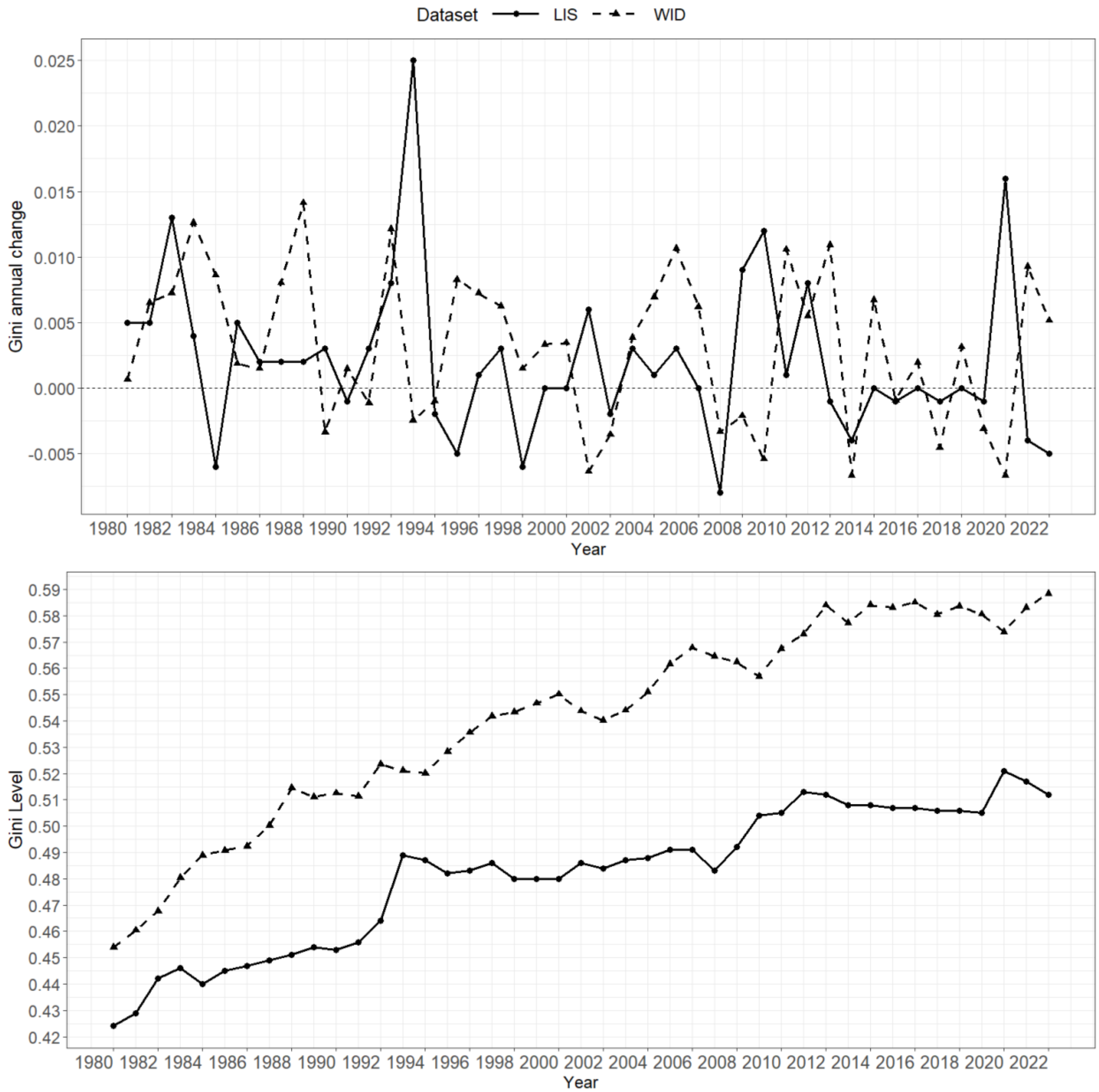

Figure 5. Gini coefficient in the United States (1980-2022). This Figure shows the actual annual change (top panel) and level (bottom panel) of the pre-tax income Gini coefficient during the period 1980-2022, using both the World Inequality Dataset (WID) and the Luxembourg Income Study (LIS) data.

The relevance of our identification of systemically significant sectors for inequality depends on the magnitude of changes in inequality induced by sectoral price shocks. To interpret the simulated changes in the Gini, we plot in Figure 5 the actual change and level of the pre-tax income Gini coefficient for the US economy. We use two alternative sources: the World Inequality Database (WID) and the Luxembourg Income Study (LIS)[9], from 1980 to 2021, a period generally characterized by a sustained increase in inequality. Both data series show the same rising trend holds for the Gini. During the four decades, the pre-tax income Gini coefficient increased by 0.1292 points according to the WID and by 0.0930 according to the LIS, with an average annual increase of 0.0031 (WID) and 0.0023 (LIS). The largest increases took place during the 1980s and 1990s, with average annual increases of 0.0059 and 0.0038 according to the WID, respectively, and of 0.0029 and 0.0027 according to the LIS. To situate the change in inequality that results from sectoral price shocks, the values of the average annual change of the Gini for the whole period are included in Figure 7.

9 Both sources use households as the unit to calculate the income Gini coefficients but differences arise from the ways in which they estimate per capita income within each household. The Gini based on the WID data calculates per capita income within a household by simply dividing the total household income by the number of members. Because of this, the population type is called "equal splits adults". The LIS income data is "equivalized" to account for the economies of scale in consumption associated with larger households. The logic for the adjustment is that, given a certain nominal income, consumption possibilities are greater for individuals living in larger households than in smaller ones. The specific adjustment is done by dividing the total household income by the square root of the household members. Each household member is assumed to have that level of income. Moreover, while the LIS primarily relies on household survey data, the WID indicators utilize a diverse range of sources, including surveys, tax records, and other administrative data. This comprehensive approach enables a more accurate estimation of income among the wealthiest households, which are often underreported and underestimated in traditional household survey data (Hasell & Arriagada, 2023).

Figure 6. The figure shows the sectoral price volatility of each industry during the period 2000-2019 (yellow dot, bottom x-axis), the associated overall inflation impact (length of the blue bar, upper x-axis), and the simulated effect of the price shock on the Gini coefficient (pink bar, upper x-axis). Industries are arranged in descending order according to their effect on the Gini coefficient. The star (*) and the plus sign (+) mark the sectors that are systemically significant for inflation or inequality, respectively. Sources: BEA input-output accounts, BEA Personal Consumption Expenditure bridge, BEA

chain-type price indexes for gross output by industry, BLS Distribution of Personal Consumption Expenditures. BLS 2020 Consumption Expenditure Survey.

Considering the price shocks in 2022, *Petroleum and coal products* has by far the largest realized effect on the Gini (0.0009), which is 29% of the average annual increase in the Gini during 1980-2021 according to the WID, and 39% according to the LIS. In other words, our results suggest that this shock to one subsector of the energy sector alone is equivalent to around a third of the annual increase in income inequality in the neoliberal decades. The food and agriculture sectors (*Farms* and *Food and beverages and tobacco products*) rank next, both with an effect on the Gini of 0.0006. That is, the effect of these sectors is around two-thirds of that of *Petroleum and coal products*. Ranks three and four are held by *Hospitals* and *Oil and gas extraction,* with an effect on the Gini of 0.0004 each, which is almost half the effect of *Petroleum and coal products* or of 12.9% of the annual Gini change based on WID and 17.4% on LIS. Interestingly, although the consumption gap between deciles is not as large for *Chemical products*, they make it into the top ranks (number six) because of the large price shocks they experienced. The final remark is that the top ten sectors in the ranking are a combination of the eight systemically significant sectors for inflation and the two healthcare sectors. This confirms the large overlap between the two categories seen in our previous results.

To further analyze the magnitude of an increase in inequality induced by price shocks to systemically significant sectors, we create a "composite sector" that receives a simultaneous shock, which we call SSS inequality in Figure 7. This composite sector consists of all the latently significant sectors for inequality defined in the previous section, and that are identified with a plus (+) sign in Figure 7. Note that for this composite sector we only calculate the *direct* inflation impact of the shock and the associated change in the Gini coefficient, due to the reasons presented in the *Methods* section. We use the actual price change for each of the eight sectors that form SSS, but in the figure, we report the average price change across all SSS for simplicity.

According to our simulation, the combined shock to the SSS inequality composite sector observed in 2022 Q2 would cause the Gini to increase by 0.0023. This magnitude is substantial: it is virtually the same as the average annual increase in the neoliberal decades (1980-2021) when using the LIS data and 0.76 when using the WID data. In other words, the price shock to eight sectors observed in 2022 can "compress", in a short period of time, the increase in inequality equivalent to between three fourths of a year or a whole year of neoliberalism. The effect on the Gini is also higher than the average annual increase in the two decades of the twenty-first century (2001-2010 and 2011-2020) according to the WID (0.0017 and 0.0006) and virtually the same as the change between 2001-2010 according to the LIS (0.0025) and greater than the change between 2011-2020 (0.0001). So, from the perspective of the experience of the past decade, the sudden increase in inequality from this group of sectoral price shocks is large.

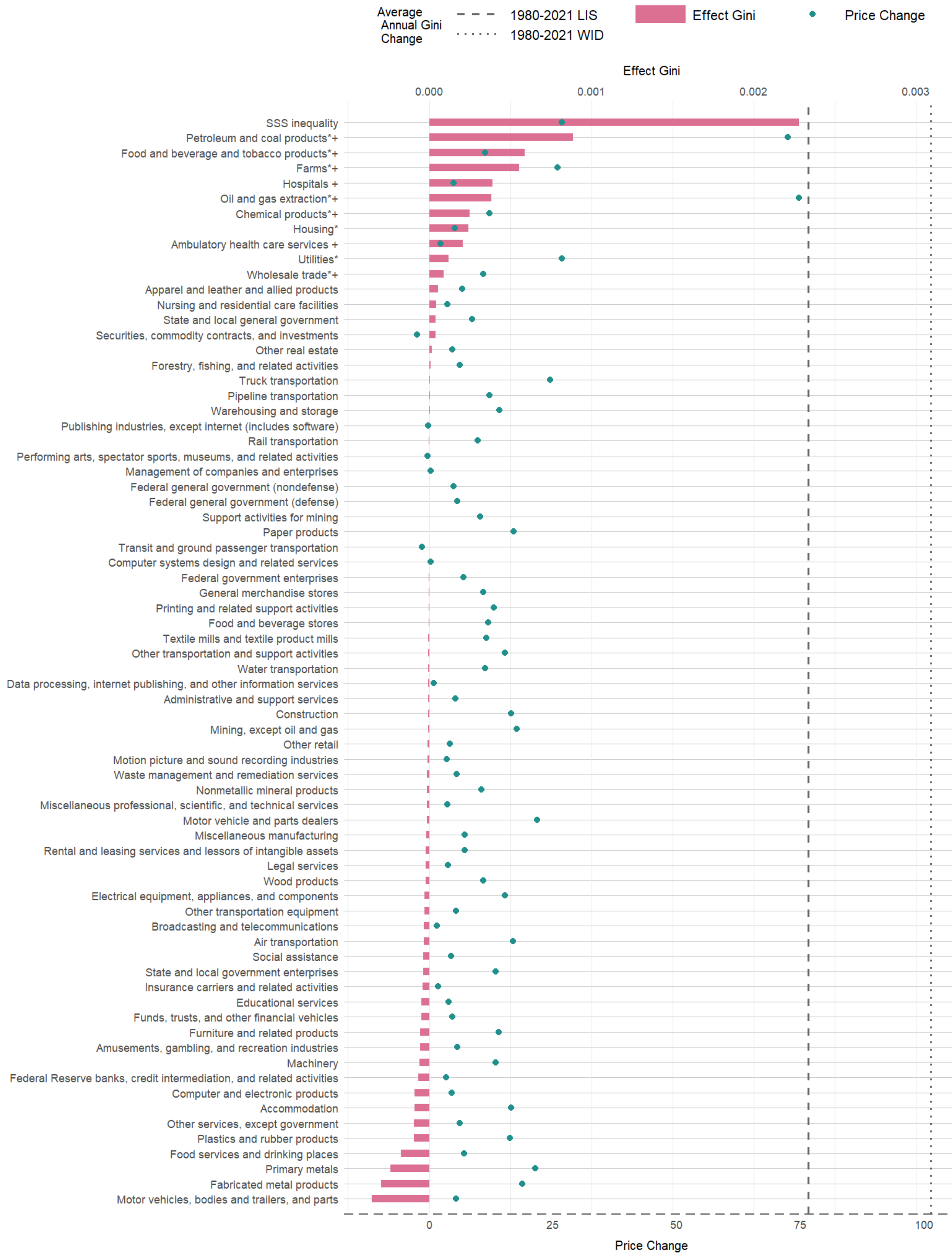

Figure 7. The figure shows the observed price changes from 2021 Q2 to 2022 Q2 (blue dot, bottom x-axis), and the associated effect on the income Gini coefficient (pink bar, upper x-axis) for each sector. The upper bar represents the effect on the Gini of the combined price shock to the eight systemically significant sectors for inequality (SSS for inequality). This effect on the Gini was calculated considering *exclusively* the direct inflation impact of the joint price shock. The vertical lines represent the actual average annual change in the pre-tax income Gini coefficient for each of the four decades between 1980 and 2021, as well as for the whole period. Sources: BEA input-output accounts, BEA Personal Consumption Expenditure bridge, BEA chain-type price indexes for gross output by industry, BLS Distribution of Personal Consumption Expenditures. BLS 2020 Consumption Expenditure Survey. World Inequality Database.

5. Conclusion and policy discussion

This paper introduces a novel framework to estimate the inequality effects of sectoral price shocks in the United States. By extending the input–output price model developed by Weber et al. (2024) and combining it with income deciles consumption expenditures data, we simulate the total (direct and indirect) impact of sector-specific price shocks on the Gini coefficient.

We find that a small number of sectors have a disproportionate potential to increase inequality through price shocks. Energy (oil, gas and petroleum products), agriculture and food, healthcare, chemicals, wholesale trade and housing, stand out as either highly volatile, essential to low-income household consumption, or crucial as intermediate inputs for other parts of the economy. These sectors exhibit a large direct inflation impact due to their high budget shares among poorer relative to richer households and, in some cases, a sizable indirect effect because of their importance as inputs for the rest of the economy. Except for the two healthcare sectors, they were also found to be systemically significant for inflation by Weber et al. (2024). In our simulations, the combined 2021–2022 shock to the eight latent significant sectors for inequality produces an increase in the Gini coefficient equivalent to nearly a full year of the average inequality growth observed during the neoliberal era (1980–2021). In other words, price shocks in a few critical sectors can, on the one hand, generate substantial increases in the overall price level, and on the other, replicate, within months, the typical annual deterioration in income distribution that has unfolded in the last decades, characterized by growing income inequality.

As discussed earlier, conventional monetary policy proves both ineffective and socially costly when used to combat cost-push inflation, particularly when the latter arises from shocks in a few essential sectors. Moreover, as noted in the introduction, such policies are far from neutral: they can actively exacerbate income inequality. Combined with our empirical results, this underscores the limits and pervasive collateral effects of conventional price stabilization policies based on interest rate hikes and highlight the need for an alternative policy toolkit. Broadly speaking, these policies should address the causes of price shocks at multiple levels and be adapted to the particular circumstances in which those shocks occur. This conclusion is in line with other empirical and theoretical analyses of the most recent inflation episode that were discussed in this paper.

At the longest-term level, large-scale investments are needed to increase the resilience of systemically significant sectors to shocks as well as their productive capacity in general. Secondly, supply-management policies—based on buffer stocks and stockpiling of different kinds—can be useful in normal times to reduce the intrinsic volatility of certain essential prices. The general logic of buffer stocks is simple: they buy when prices fall, and they sell when prices increase to try to keep them within certain limits (Weber & Schulken, 2024). In emergencies, they can become crucial to prevent large price spikes that, in turn, can propagate across the economy. Finally, beyond direct supply-management intervention, prices can also be influenced either indirectly (through subsidies, tax breaks, and similar measures affecting production costs) or directly via price controls, which can take the form of price corridors, caps at different stages of the supply chain, or other more sophisticated policies of price regulation. Direct price controls can be socially optimal once a shock has already occurred, as they constitute emergency measures that "buy time" for supply to adjust without exposing households and firms to the full consequences of a large price spike (Galbraith, 1952).

The optimal design of all these policies depends on several factors, including the nature of the product (e.g., whether it can be stored for long periods), the market structure (e.g., how producers react to cost changes), and the specific conditions of the industry in each particular country (e.g., whether it produces the good domestically or depends heavily on imports). Although these policies were at best marginal in most advanced economies prior to 2022, they have since become the focus of both academic and policy debate, and in some cases have already been implemented or had existed for a long time. They are particularly common in energy and food, given the widespread recognition of their economic and political importance.

In Germany, for instance, the government responded to the 2022 energy crisis by purchasing natural gas reserves, rejecting a full embargo on Russian gas, and introducing an "energy price brake" in early 2023; while these measures prevented a large-scale shortage, their effects were limited by late timing and sub-optimal design (Krebs & Weber, 2024). Similar interventions were adopted elsewhere in Europe: Spain and Portugal introduced the Iberian exception mechanism (IbEx), a cap on the gas price used in electricity generation, which helped reduce retail electricity prices by 40% and significantly lowered inflation in Spain (Haro Ruiz et al., 2024).

In Mexico, state ownership of the main oil and fuel company (PEMEX) facilitated interventions that kept fuel price increases below those observed in the United States (Matamoros et al., 2025). In addition, the government reached an unbinding agreement with firms to cap the price of a basket of essential goods, primarily food products, which was complemented by the deployment of strategic grain reserves and the temporary elimination of import tariffs on fertilizers and other goods.

China maintains a permanent and comprehensive system of supply management and price stabilization in essential goods. In energy, state-owned enterprises, retail price ceilings, and strategic stockpiles cushion international volatility, while coal and electricity operate under a dual-track pricing system in which part of output trades at market prices, but a regulated share is supplied at capped rates to guarantee affordable electricity for households. In food, the government deploys fertilizer reserves, grain stockpiles, "vegetable basket" programs, and pork reserves to smooth seasonal or cyclical price fluctuations. These mechanisms of supply management and price controls help explain China's ability to maintain price stability even during periods of global inflationary turbulence (Weber et al., 2025).

These cases show that sector-specific price stabilization and supply resilience policies are feasible to implement, but further research is necessary to come up with the optimal design for each specific industry and country. Overall, our research suggests that the inflation control policy framework must go beyond broad aggregates like the CPI and instead engage with the structural origins of price changes, desirable not only for reasons of equity and social justice, but also for the promotion of more stable and sustainable economic growth (Berg et al., 2018; Cingiano, 2014; Halter et al., 2014). In doing so, policymakers can curb inflationary pressures while directly mitigating the disproportionate burden on the poor.

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Appendix A. Summary of the Quantitative Results

Table A1. Summary of results for systemically significant sectors for inflation and inequality

Code	Description	Income Group	Consumption Share 2019 (%)	Consumption Share 2021 (%)	Inflation Impact Sectoral Price Volatility 2000-2019	Inflation Impact Annual Price Change 2021 Q2- 2022 Q2	Effect on the Gini Sectoral Price Volatility 2000-2019	Effect on the Gini Annual Price Change 2021 Q2- 2022 Q2
111CA	Farms	Bottom	0.94	1.04	0.26	0.77	0.000195	0.000555
		Middle	0.73	0.82	0.21	0.61		
		Top	0.48	0.55	0.14	0.44		
211	Oil and gas extraction	Bottom	0.07	0.12	0.25	0.87	0.000135	0.000382
		Middle	0.05	0.09	0.21	0.77		
		Top	0.03	0.06	0.17	0.65		
22	Utilities	Bottom	1.61	1.67	0.14	0.73	0.000009	0.000119
		Middle	1.57	1.60	0.13	0.71		
		Top	1.54	1.38	0.13	0.65		
311FT	Food and beverage and tobacco products	Bottom	6.32	6.57	0.25	0.83	0.000182	0.000589
		Middle	4.75	4.92	0.20	0.64		
		Top	3.13	3.34	0.14	0.47		
324	Petroleum and coal products	Bottom	1.88	1.57	0.57	1.65	0.000375	0.000886
		Middle	1.48	1.24	0.48	1.41		
		Top	0.89	0.88	0.34	1.14		
325	Chemical products	Bottom	2.79	2.52	0.20	0.47	0.000123	0.000249
		Middle	2.46	2.34	0.18	0.44		
		Top	1.56	1.49	0.13	0.33		
42	Wholesale trade	Bottom	4.80	4.84	0.14	0.94	0.000040	0.000088
		Middle	4.44	4.47	0.13	0.89		
		Top	3.67	4.29	0.12	0.88		
621	Ambulatory health care services	Bottom	10.52	9.87	0.10	0.22	0.000087	0.000209
		Middle	7.92	7.80	0.07	0.18		
		Top	4.99	4.67	0.05	0.11		
622	Hospitals	Bottom	8.80	8.33	0.07	0.41	0.000067	0.000389
		Middle	6.60	6.56	0.05	0.33		
		Top	4.12	3.89	0.03	0.19		
HS	Housing	Bottom	16.05	16.76	0.16	0.88	0.000008	0.000242
		Middle	15.66	16.09	0.15	0.84		
		Top	15.35	13.79	0.15	0.72		

Note: The table presents the consumption share and total inflation impact for each of the sectors identified as systemically significant for inflation and inequality associated with the sectoral price volatility between 2000 and 2019 and the annual price change between 2021 Q2 - 2022 Q2. It also shows the effect on the Gini coefficient associated with these shocks.

Appendix B. Input-Output and Personal Consumption Expenditures categories

Table B1 lists the 71 sectors into which the U.S. economy is divided in the Input-Output tables published by the BEA, which are based on the North American Industry Classification System (NAICS). In contrast, Personal Consumption Expenditures (PCE) follow the classification used in the National Income and Product Accounts (NIPA). The specific expenditure categories used in the distributional PCE dataset—which reports spending in each category by income decile—are shown in Table B2. The PCE bridge, provided by the BEA, indicates how expenditures in NIPA categories correspond to the NAICS sectors listed in Table B1. This correspondence makes it possible to derive decile-specific consumption shares for each Input-Output sector.

Table B1. Bureau of Economic Analysis Input-Output sectors

Code	Description	Code	Description
111CA	Farms	486	Pipeline transportation
113FF	Forestry, fishing, and related activities	487OS	Other transportation and support activities
211*	Oil and gas extraction	493	Warehousing and storage
212*	Mining, except oil and gas	511	Publishing industries, except internet (includes software)
213	Support activities for mining	512	Motion picture and sound recording industries
22	Utilities	513	Broadcasting and telecommunications
23	Construction	514	Data processing, internet publishing, and other information services
321	Wood products	521CI*	Federal Reserve banks, credit intermediation, and related activities
327	Nonmetallic mineral products	523*	Securities, commodity contracts, and investments
331	Primary metals	524*	Insurance carriers and related activities
332	Fabricated metal products	525*	Funds, trusts, and other financial vehicles
333	Machinery	HS*	Housing
334	Computer and electronic products	ORE*	Other real estate
335	Electrical equipment, appliances, and components	532RL	Rental and leasing services and lessors of intangible assets
3361MV	Motor vehicles, bodies and trailers, and parts	5411	Legal services
3364OT	Other transportation equipment	5415	Computer systems design and related services
337	Furniture and related products	5412OP	Miscellaneous professional, scientific, and technical services

339	Miscellaneous manufacturing	55*	Management of companies and enterprises
311FT	Food and beverage and tobacco products	561	Administrative and support services
313TT	Textile mills and textile product mills	562	Waste management and remediation services
315AL	Apparel and leather and allied products	61	Educational services
322	Paper products	621	Ambulatory health care services
323	Printing and related support activities	622	Hospitals
324	Petroleum and coal products	623	Nursing and residential care facilities
325	Chemical products	624	Social assistance
326	Plastics and rubber products	711AS	Performing arts, spectator sports, museums, and related activities
42	Wholesale trade	713	Amusements, gambling, and recreation industries
441	Motor vehicle and parts dealers	721	Accommodation
445	Food and beverage stores	722	Food services and drinking places
452	General merchandise stores	81	Other services, except government
4A0	Other retail	GFGD	Federal general government (defense)
481	Air transportation	GFGN	Federal general government (nondefense)
482	Rail transportation	GFE	Federal government enterprises
483	Water transportation	GSLG	State and local general government
484	Truck transportation	GSLE	State and local government enterprises
485	Transit and ground transportation		

Note: Industry codes and descriptions for the US input-output table. Industry codes with an asterisk are assumed exogenous in all our simulations, this means that their price is assumed to be fixed and thus unaffected by the output prices of other industries. Source: Bureau of Economic Analysis.

Table B2. Personal consumption categories

Personal Consumption Expenditure Category
Motor vehicles and parts
Furnishings and durable household equipment
Recreational goods and vehicles
Other durable goods
Food and beverages purchased for off-premises consumption
Clothing and footwear
Gasoline and other energy goods
Other nondurable goods
Housing and utilities
Health care
Transportation services
Recreation services
Food services and accommodations
Financial services and insurance
Other services
Final consumption expenditures of nonprofit institutions serving households (NPISHs) (132)*

Note: The table shows the categories of the Personal Consumption Expenditures approach used for all calculations in the paper. Source: Bureau of Labor Statistics.
*This category is not present in the bridge between the NAICS and the personal consumption categories. For the analysis, the personal consumption expenditure in this category is assumed to be zero and new shares are calculated based on that assumption.