Sharing is Caring: Inequality, Transfers, and Growth in the National Accounts

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Abstract

Using the updated Distribution of Personal Income by the Bureau of Economic Analysis for U.S. households (2007-2018) with a focus on the bottom of the distribution, I show that transfers significantly lower the level of pre-tax and post-tax inequality in a National Accounts framework. However, 2/3 of the reduction in the Gini derives from Social Security and Medicare. Though mostly available to elderly households, together these programs quadruple the share of the bottom income quintile and reduce the Gini by 16%. Conversely, the inclusion of all means-tested programs (such as Medicaid and refundable tax credits) reduces the Gini by half as much, raises the share of the bottom quintile by only 1.8 percentage points, and does not increase the income share of the middle quintiles. Consistent with an aging population, transfers have increased as a share of personal income; yet, inequality continues to rise.

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I. Introduction

At the meetings of the American Economic Association (2020), Angus Deaton remarked "We need to know, not only how national income changes, but who receives it." (Deaton 2020) His statement echoes calls for metrics to measure well-being, rather than production (Stiglitz et al. 2018). As the Bureau of Economic Analysis (BEA) releases estimates of Gross Domestic Product (GDP), questions about distribution of income persist: is mean household income growing as fast as GDP (or GDP per capita)? The BEA has produced an updated Distribution of Personal Income for households to assess the relationship between the distribution of growth and trend in inequality.[2] These metrics are an important compliment to GDP; they tie income inequality to growth by showing whether growth was higher (or lower) for those at the top (or bottom) of the income distribution.

To assess how growth is shared among households, Fixler, Gindelsky, and Johnson (FGJ) 2020 consider multiple inequality measures. Moving beyond the Distributional National Accounts (DINA) literature focused on top shares (see Auten and Splinter (A&S, 2019) and (recently updated) Piketty, Saez, and Zucman (PSZ, 2018))[3], they find that though all income quintiles shared in the growth in personal income (PI) and disposable personal income (DPI) (22% total increase for both, 2007-2018), overall inequality rose slightly. Over half of income is received by the top quintile, as well as over half of the growth over the period. Thus their share of PI rose by 2 percentage points (pp). Is a 2pp difference in the top quintile economically meaningful? If the top 20% share were to increase in 2018 from 51%-53%, for example, the top quintile (approximately 25 million households in 2018) would have $330 billion more in PI (each top quintile household has $13,200 more). If instead that $330 billion were distributed to the bottom 80% equally, each household would receive an average of $3,250, 4x less.

These back-of-the-envelope calculations lead to the immediate question: redistribution is seldom done uniformly, so what is the real effect of transfer programs on inequality? In this exercise, I extend the analysis of FGJ (2020) to assess the specific role that transfers play in reducing inequality of PI, highlighting which are the most impactful. I find that the inclusion of all transfers in PI (2018) reduces the Gini by 25% from 0.6 to 0.45 and increases the income shares of the bottom quintiles: 0.8%-5.2% for the 0-20%, and 5.4%-9.1% for the 20-40%. However, 2/3 of the decrease in the Gini and over half of the

[2] The BEA's predecessor (the Office of Business Economics) estimated the distribution of personal income for the 1940s, and the BEA followed those estimates regularly from 1950-1962 (Fitzwilliams (1964)). The latest estimates published before the current estimates were produced for 1971 (Radner and Hinrichs (1974)).

[3] FGJ top income shares (1% and 5%) fall in between A&S and PSZ, despite stark differences in data and methodology.

rise in bottom quintiles is solely due to the addition of Social Security (SS) and Medicare (together they are 55% of the transfer total). As these programs are mostly available to elderly households (here defined as those with at least one member age 65+) and elderly households also participate in other transfer programs, this shows that transfer programs primarily redistribute income from younger households participating in the labor force to the elderly. As the population ages (baby boomers retire), the share of elderly households grows (24%-32% from 2007-2018), increasing program utilization and income share. Conversely, the programs which redistribute income from high-income households to low-income households (such as means-tested programs, including Medicaid, and refundable tax credits) in total reduce the Gini by an additional 9.5%, raise the share of the bottom quintile by only 1.8pp, and do not increase the income share of the middle quintiles.

There are two distinct features of this analysis, as compared with existing DINA exercises focused on top shares of NI, which make it possible to isolate the transfers most effective in reducing household inequality. First, by distributing PI and DPI, I am using the NA concepts closest to the measure of economic resources available to households for consumption, more appropriately identifying the role of transfers. Second, by using the CPS as the base dataset (with corrections for underreporting of certain transfers), I am able to analyze impacts on many low-income households and non-filers.

I show that these salient trends are broadly consistent with those calculable of PSZ , A&S, and CBO, and that they are economically meaningful. This paper proceeds as follows: Section II discusses the measurement of income, while Section III provides an overview of the data and the methodology. Sections IV presents the results and discussion, including a comparison to other estimates. Section V concludes.

II. Income Measurement

In recent years, many studies have focused on inequality and growth including PSZ (2018), Boushey and Clemens (2018), OECD (2014), and Ostry (2014). There is a broad consensus that inequality has risen in the United States since 1980, independent of the metric used (Piketty, Saez, and Zucman 2003; CBO 2013; Johnson and Smeeding 2014). However, views differ on the magnitude of the rise and the effects on macroeconomic growth (OECD 2012; OECD 2014; Grigoli 2014). Opinions also differ as to whether inequality can (or should) be measured by consumption, income, or wealth.[4] A foundational reason for the controversy is that seemingly subtle disparities in datasets, definitions, and methodology can yield markedly different results. Income can be defined to include treatments of imputed income, capital gains (realized and unrealized), unrealized interest on property income and government (and in-kind) transfers. Whether we allocate that income to households, individuals, or tax units can lead us to conclude that income inequality is increasing or decreasing.

Identifying the purpose of the estimates is a crucial step in choosing a dataset, definition, and methodology. Is our goal to accurately measure inequality overall? To quantify what resources households have for consumption? To evaluate the impact of policies focused on redistribution (e.g., taxes and transfers) on household income levels and mobility?

The BEA's chosen metric, PI, is the most appropriate measure of income received by households participating in production in the national accounts.[5] It is closely related to aggregate growth, comprising 87% of Gross Domestic Income (GDI). "*Personal income is the income that persons receive in return for their provision of labor, land, and capital used in current production, plus current transfer receipts less contributions for government social insurance (domestic)." (Source: NIPA Handbook, CH.2 (BEA 2017))* It does not include capital gains or retirement income.[6]

Given that the purpose of this exercise is to assess the role of transfers, it is preferable to choose a NA definition as close as possible to the resources available for consumption (pre-tax PI or post-tax DPI). As PSZ (2018) and A&S (2019) distribute a different NA aggregate (NI),[7] their exercises necessitate distributing government expenditures on public goods to households. While PSZ include this expenditure in transfers, it is extremely difficult to arrive at an appropriate proportional distribution. PSZ also emphasize that the inclusion of transfers without subtraction of taxes is less meaningful, given that the transfers are funded by taxes. I am able to compare DPI directly to post-tax-and-transfer results of PSZ and others, while keeping the focus on the income received by individuals for consumption. PI is tied to Personal Consumption Expenditures (PCE) conceptually.[8]

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[4] One way that income, consumption, and wealth can be related is to use an early indicator of well-being: The Haig-Simons concept of income. It can be stated as Income = Consumption + Change in Asset Value (Haig 1921; Simons 1938).
[5] PI and DPI are released monthly by the BEA, along with PCE.
[6] Personal income can also be expressed as the sum of two components: household income plus income received by nonprofit institutions serving households (NPISH).
[7] Unlike PI, NI Income includes corporate profits, taxes on production, contributions for social insurance, net interest, business current transfers, current surplus of government enterprises, but *excludes* PI receipts on assets and current transfer receipts.
[8] Empirically, deflating PI by PCE allows me to evaluate growth over time in real terms.

With most metrics, such as the Gini, the higher the value, the more unequal the distribution. As top shares increase, the Gini generally increases as does the share of income held by the upper quintiles (at the expense of the lower quintiles), but not always. For example, the top 1% share of PI increased from 11.7%-12.3% (2009-2010), but the Gini decreased from 0.432 to 0.429. In fact, the bottom gained slightly in that year (increased transfers), while the share of the 80-95% decreased 0.5pp, leading to this outcome.[9] By focusing on movements in either the top shares, or the Gini, it is easy to miss important distributional changes. As such shifts are particularly relevant when evaluating the impact of transfers, I will be looking at all quantiles of the distribution, in addition to the Gini and top shares.

III. Data and Methods

This paper builds on the methodology to allocate personal income developed recently in FGJ (2020). This methodology is summarized below in section A. Section B describes the methodology to evaluate the impact of transfers, time trends, and comparisons with other metrics.

A. Distributing personal income: FGJ (2020) methodology overview

FGJ (2020) use survey and administrative data to allocate NIPA totals to households. Beginning with the Current Population Survey (CPS ASEC, March Supplement) and supplementing with other datasets, variables are used to impute values for each component of PI directly to the relevant households. Consistent with previous exercises (Fixler and Johnson 2014; Fixler et al. 2017; FGJ 2018; FGJ 2019), the analysis starts in 2007 (collected in 2008) due to the availability of explanatory variables in component datasets (particularly CMS). These datasets include:[10]

- *IRS Statistics of Income:* Aggregate 1040 data stratified by AGI (2007-2018).
- *Congressional Budget Office:* CPS crosswalk for Medicaid, SNAP, and SSI to address known underreporting (Meyer et al. 2015, Meyer and Mittag 2019) (2007-2018)
- *Consumer Expenditure Survey:* Imputation of rental equivalence for owner-occupied housing (2007-2018).
- *Survey of Consumer Finances:* Allocation of imputed Interest income (2007-2019, every 3 years).
- *Centers for Medicare & Medicaid Services:* Average annual expenditure for Medicare by state (2007-2018).

[9] The pattern is the same for DPI in 2009-2010.
[10] More detail on how each dataset is used is in Gindelsky (2020).

- *Medical Expenditure Panel Survey*: Allocation of employer contribution to health insurance (2010-2018).

There are three main steps to allocate the NIPA totals. For a detailed description of each, please see Gindelsky (2020). These steps are:

1) Identify a NIPA component total to be distributed,[11]

2) Identify a CPS variable(s) (and/or supplementary variables from outside data sources) which can be used to allocate this total to households, using the distribution of the aforementioned variables,[12] and

3) Sum all household components to subtotals of interest, PI, and DPI[13]

After personal income has been computed, it is adjusted for household size through the following formula:

$$Equivalized\ Personal\ Income = \frac{Personal\ Income}{\sqrt{\#\ HH\ members}}$$

FGJ (2020) equivalize in order to account for resource and income sharing in households of different sizes. This reduces top shares and income inequality overall. Alternative equivalence scales are possible, such as those of the Census Bureau and OECD, which weight adults more than children, or that of PSZ (2018), who divide by the number of adults over age 20. Although the effects of different equivalization methods are very visible in levels (means), they do not meaningfully affect inequality results in most cases.[14]

B. Decompositions and Comparisons

As in FGJ (2020), I initially decompose household income into Adjusted Money Income (AMI), Financial Items (F), Health Items (H), and Other Transfers (net) (T). AMI comprises approximately 2/3 of personal

[11] NIPA components of personal income are laid out in NIPA Table 2.9.

[12] An important part of the calculation includes adjusting the top incomes of the CPS (i.e., "the tail") to correct for underreporting. Previously, FGJ had calculated a Pareto coefficient for incomes of at least $500,000 from IRS 1040 micro data in order to impute a distribution onto CPS public-use data (Fixler, Gindelsky, and Johnson 2019). An alternative strategy was used in FGJ (2020) in order to maximize transparency and replicability for data users. For each of six CPS variables which are available in the SOI data (wages, business income, interest income, dividends, farm income, and rents and royalties), the corresponding CPS variable was first summed. Then the difference between the NIPA total for that variable and the CPS total (i.e., the "extra") was allocated proportionally to constructed tax units whose (re-calculated) AGI were either below (or at least) $500k according to the share of IRS tax income below (or above) $500k. Top shares calculated after this tail adjustment closely matched those calculated from the earlier pareto adjustment. For more detail on this methodology, please see Gindelsky (2020).

[13] To move from Household Income to Personal Income, we deduct *Household Current Transfer Receipts from Nonprofits and Nonprofit Institution Transfer Receipts from Households* and add *Nonprofit Institution Income*. This residual is distributed equally to all households in the CPS and constitutes <0.1% of Personal Income.

[14] While there is some variation in inequality levels, the overall conclusions about the distribution, or time trend, do not change.

income. The majority (approximately 95%) of AMI derives from labor income (e.g., wages, business income, etc.), investment income (e.g., interest, dividends), and social security income.[15] Financial items consist of employer contributions for pension plans and life insurance, imputed interest and dividends received, and rental income from owner-occupied housing. Health items consist of Medicare and Medicaid, employer contributions for health insurance (including for military), and medical assistance for low-income families.

In order to isolate the transfers, I add all transfers contained in AMI and H, such as SS, unemployment insurance, Medicare, etc. to T, which consist of net transfers that are not already counted in the previous categories (AMI and H; F contains no transfers), including refundable tax credits in addition to assistance programs such as SNAP, WIC, energy assistance, educational assistance and others.[16]

I then construct the income distribution without transfers and iteratively add transfers in order of economic significance (size): SS, Medicare, Medicaid, Tax Credits, Other Means-Tested Transfers (MT), and finally other remaining transfers to arrive at PI (or DPI). With each transfer addition, I equivalize and re-rank households in order to see the change in the distribution.

IV. Results

The results of this exercise have a great deal to tell us about the relationship between inequality, transfers and growth, both in level and in trend. I will first look at the change in inequality of PI over the period, and then at the composition of PI, decomposing transfers. Finally, I will compare these results with those of other DINA estimates and the CBO.

A. Overall Inequality Levels and Trends

Figure 1 shows a slight increase in inequality for PI over the period (For DPI, see Appendix Figure A1). The share of the top quintile increases (including the top 1%) as the share of the other quintiles falls.[17] Through

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[15] Most of the remaining 5% is made up of rents and royalties, unemployment insurance, and disability income.
[16] Employer and employee contributions for government social insurance are netted out in the subtotal for this category, although they are included in other Table 2.9 line item subtotals that are subsequently distributed.
[17] It is important to note that a CPS redesign in this period (incorporated in parts in 2014 and 2018 in the BEA analysis) does contribute to part of the increase in top shares, as it raises topcodes in addition to questionnaire changes. However, using tax data, PSZ (2018) and A&S (2019) find increases in the share of the top 10% and decreases in the bottom 50%. Though CBO (2020) finds a decrease in the top 10% (driven by a decrease in the top 1% share), it seems unlikely that the increase in inequality is entirely the result of the redesign.

an initial comparison of pretax PI and post-tax (DPI), we can conclude that the inclusion (or exclusion) of taxes does not change the broad isolate the effect of taxes on the distribution, before we turn to the impact of transfers. Though the level of inequality is a bit lower and the changes are a bit less volatile for DPI, the trend is the same as that of PI. Thus, taxes do redistribute income somewhat, lowering top shares and increasing bottom shares by a couple percentage points.

B. Composition of PI

Next, we can evaluate how the composition of PI is tied to inequality in both levels and trend in Figures 2 and 3, respectively (data for all years in web appendix at mgindelsky.com). Though transfers are 17.5% of income overall in 2018 (up from 15.5% in 2007),[18] Figure 2 shows that they are a significantly greater portion of the bottom quintiles (around half) and an almost insignificant share of the top quintile (6%). Conversely, AMI (consisting of labor earnings, interest, dividends, and rental income) is the majority of income for the top quintiles but only 1/3 for the bottom quintile. Financial income (mostly composed of employer contributions to pensions and insurance, in addition to imputed interest and dividends), grows as a share of income across the distribution, becoming nearly 20% for the top quintile.

Looking closer at the share of transfers specifically by decile in Panel A of Figure 3, it's clear that transfers are even bigger (smaller) at the bottom (top) of the distribution, and grew significantly for lower quintiles over the period (54%-64% of PI for the bottom decile). Panel B of Figure 3 illustrates an interesting contrasting impact of transfers on inequality; in levels, transfers reduce inequality (note the increase in the share) but over time, an increased share of transfers is correlated with growth in inequality. Panel C plots PI quantiles with and without transfers over time. It illustrates that though the inclusion of transfers raises bottom shares and lowers top shares, there is little impact on the middle of the distribution and that the inclusion of transfers does not attenuate the trend in inequality.[19] To understand why this pattern emerges, it is helpful to look at not just aggregate transfers, but their composition.

C. Composition of Transfers

[18] The share of transfers in this chart includes the share of PI from the NPISH adjustment (0.1-0.2%).
[19] For a recent study of mechanisms influencing transfer impacts on the middle class, see Looney et al. (2020).

Figure 4 decomposes the effect of transfers by adding them iteratively in order of economic significance (size) for 2018. Though we will focus on the results for PI, the results for DPI are very similar (See Appendix Figure A2). First adding SS, it's clear that SS has a big impact on inequality.[20] The Gini falls by 10% and the shares of the 0-20% and 20-40% quintiles rise by 200% and 30% respectively, at the shares of the top 2 quintiles fall (especially the top quintile). This is a strong redistributive effect. Subsequently adding Medicare further increases bottom shares by an additional 30% and 11% for the 0-20% and 20-40%, respectively, as the top quintile falls further (with a slight decrease in the 60-80% as well). Together, SS and Medicare reduce the Gini by 2/3 and increase the share of the bottom two quintiles by 4.7pp, or 76%, and the middle quintile (40-60%) by 1pp. These are very significant impacts.

Turning to income-related transfers, I iteratively add Medicaid, refundable tax credits, and other remaining means-tested transfers (such as SNAP, WIC, etc.). The addition of Medicaid further increases the share of the bottom two quintiles by 2pp as the share of the upper 2 quintiles drops, with virtually no change in the share of the middle 40-60%. The subsequent additions of tax credits and other means-tested transfers raise the bottom quintile an additional 0.5pp, but barely change the distribution (only lowering the Gini 0.014).

As Figure 4 shows, most of the reduction in inequality from the addition of transfers derives from SS and Medicare.[21] As these programs constitute 55% of total transfers in NIPA in 2018 (and 64% for the middle income quintile), it is consistent to see a large effect on inequality vs. Medicaid, which is 20% of transfers overall (and only more for the bottom quintile). The massive reduction in poverty from these programs is well-documented in Meyer and Wu (2018). However, SS and Medicare are programs mostly available to those ages 65+.[22] The share of households benefiting from these transfers has increased from 2007-2018 (see Figure 5) and is highest for the 20-40% income quintile. As the baby boomers continue to retire, we expect this share to increase in the next decade, resulting in an even greater impact of SS and Medicare on the income distribution.

To better understand the impacts of the transfers available to those under-65, I decompose Figure 4 by age in Figure 6. Panel A iteratively adds the same transfers for only elderly households, while Panel B does so for only non-elderly households. In Panel A, SS and Medicare reduce the Gini by 50% for elderly

[20] Meyer and Wu (2018) have an excellent discussion of these transfer programs and highlight the overwhelming importance and impact on poverty reduction of SS for elderly households.

[21] Moon and Wang (2016) also show a significant redistributive effect of these programs using CPS data.

[22] There are some who meet criteria for Medicare eligibility who are under 65 (and non-elderly households who benefit from SS, including children). BEA allocates Medicare expenditure by state separately for those ages 65+ and under 65.

households and reduce the share of the upper quintile by 12.7pp, while the addition of all other transfers results in a small further inequality reduction (0.025 change in the Gini). As Gornick and Milanovic (2015) point out in their analysis, the elderly shift from relying on market income to transfers, but less so than in European countries.

As expected, the additions of SS and Medicare have a smaller (but still positive) impact on the younger households (only raising the share of the bottom quintile by 1pp).[23] However, we do not see as large an impact from the additional transfers as we might anticipate. The addition of Medicaid increases the bottom quintile by 1.5pp and adding the tax credits by a further 0.2pp. Overall, the addition of transfers decreases the Gini by 15%, as compared to 41% for elderly households. Moreover, post-transfer, the elderly household distribution is significantly more equal (Gini = 0.409) than that of the non-elderly households (Gini = 0.466).[24]

Since we have been looking at the distribution for the latest year available (2018), we might ask whether a significant change in transfers during the period (the Medicaid expansion) had an impact on the distribution. A priori, we might expect states that expanded Medicaid to have lowered inequality more than those that didn't, particularly for non-elderly households. While adding Medicaid did increase bottom shares and reduce top shares, this effect is hardly different between the states that expanded Medicaid and those that did not (see Appendix Table A1).[25] While overall inequality did rise slower in states which expanded (ΔGini = 0.01) compared to those who didn't (ΔGini = 0.04), average inequality in the states which expanded was initially higher (ΔGini= 0.02); these effects cancel out somewhat in national aggregate estimates.

D. Comparisons to Other Estimates

As this exercise is based on the distribution of national accounts, it makes sense to contrast the effects of transfers on inequality in comparable exercises. First, I compare the PSZ NI post-tax-and-transfer distribution (available in their published tables) to DPI in Figure 7 for 2018. The two distributions are very comparable, though BEA DPI has a higher share of the bottom 50% and PSZ has a higher share of the top 5%. However, once I compare the share of transfers in each quantile between BEA & PSZ, some

[23] Some of this impact is on younger families is due to qualification from disability status and survivorship benefits.
[24] Here it is important to note that the definition of PI does not include retirement disbursements.
[25] Table A1 shows that the drop in the Gini from iteratively adding Medicaid is almost the same for the states which expanded benefits (-0.037) as for those that didn't (-0.030). As per Census guidance, I average 3 years for state-level comparisons.

differences emerge (see Appendix Figure A3). Though the share of Medicare & Medicaid is comparable for the upper half of the distribution, it is a bit higher for the BEA DPI distribution. Conversely, the PSZ non-health transfer share is significantly higher than BEA, likely due to the inclusion of government expenditures on public goods in PSZ estimates.[26]

This leads to a different interpretation of the results. In a recent discussion of the effects of taxes and transfers, Saez and Zucman (2020) comment, "yes, but not a lot" in response to whether government intervention has increased incomes at the bottom. They further state that the gains are driven by Medicare and Medicaid (they don't consider SS a transfer), but that the gains in post-tax income to the bottom 50% come from in-kind transfers and the collective public expenditures.

I can also compare the effects from the iterative addition of transfers on published top 1% shares with Auten and Splinter (2019) (Table 1). Though the BEA effects are slightly larger (especially for SS), the overall reduction in top shares from the addition of these transfers is comparable. This is to be expected since differential effects of transfers are best observed at lower incomes.

Finally, it is useful to compare with CBO (2020) estimates. Although these estimates are not scaled to national accounts totals, CBO provides many income decompositions and focuses on the impact of transfers. First, CBO does not include Medicare and SS in its definition of transfers (instead classifying them as social insurance benefits). However, by comparing "Market Income" to "Income Before Taxes and Transfers" metrics (CBO 2020, Exhibit 22 on p. 31), a large drop in inequality is observed primarily due to the addition of SS and Medicare (CBO Gini drops 0.602-0.521 in 2017, compared to similarly defined BEA Gini drop (0.598-0.505). This corroborates the large effect of these programs found in the BEA analysis.

However, as the CBO income definition includes many things that PI does not, and excludes other items that PI includes, the distributional results (while very similar in shares of the distribution corresponding to each transfer (see Appendix Table A2)) are subsequently different. This difference likely stems from 2 key factors: (1) the scaling of transfers to national accounts raises their nominal value, particularly where they are underreported, (2) though I recalculated pre-tax income from the published CBO tables to more closely match the BEA definition, the CBO published quintiles are still ranked on their initial "income

[26] In order to compare to PSZ appropriately, I recalculated DPI to exclude SS, Unemployment Insurance, and Disability as in their "Income Net of Taxes" definition, as a starting point.

before taxes" distribution, which includes items such as capital gains,[27] that PI does not include, but will affect the ranking of households.

V. Conclusion

In sum, these results have shown that although transfers lower inequality in levels, the effect is primarily due to redistribution from younger, labor-earnings households to elderly households through SS & Medicare, with a small additional impact from Medicaid and other means-tested transfers. Rather than observing a substantial redistributive impact from higher income households to lower income households by means-tested transfers (including Medicaid), which have been the focus of so much study and policy analysis, we see that they do not have a large impact on PI inequality, even when isolating younger households.[28] Because we distribute values to households such that they sum to NIPA totals, the means-tested transfers are dwarfed by the impacts of not only SS & Medicare, but compensation. However, controlling to NIPA totals is the appropriate way to evaluate the relationship between inequality and macroeconomic growth, both pretax (personal income) and post-tax (disposable personal income). Additionally, by decomposing PI, we are able to isolate the effects of each income component (and transfer program) and relate them to consumption via PCE.

Overall, this analysis suggests that inequality would be rising significantly faster if the population were not aging at the current rate, since fewer households would be receiving large transfer payments. The period under study represents only the first half of the baby boomer retirees, who will continue to become newly eligible for benefits for another decade. Thus, it is extremely important that we understand the dynamic trends in income composition, both when analyzing past inequality trends and when predicting future trends.

Moreover, this analysis highlights the limitations of a one size fits all approach to inequality measurement. Many would like to have one number, based on one distribution, produced in real time, and providing all of the information we would like to know. However, the vast literature in this field has shown the limitations of such an approach. The advantage of decomposing PI and DPI, using the CPS as the base dataset, is the benefit of being able to impute specific transfer expenditures to low-income (often non-

[27] This is a very important and consequential difference (see Armour et al. 2014)

[28] However, this is not to say that these programs are not effective in reducing poverty, or raising incomes for those in the bottom quintiles, as many studies have shown that they do successfully (for example, Meyer and Wu 2011, Hoynes and Patel 2018).

filing) households, which in turn allows us to more accurately assess the relationship between growth and inequality. Though there is no one “right answer”, this analysis provides an important perspective which can help form a complete picture.

As the goal of this exercise is to analyze the effect of transfers on income inequality through a national accounts perspective, it is encouraging that my results are largely consistent with PSZ, A&S, and CBO once definitional differences are accounted for. However, this comparison also highlights the very important differences in DINA estimates, as compared with other income metrics. It illustrates that we must think carefully about how to define “income” and “transfers” before considering which estimates best answer our research and policy questions.

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Tables and Figures

Table 1: Iterative Addition of Transfers for Top 1% (Comparison to A&S)

	Pretax inc	+SS	+ Cash Trans	+ Medicare	Pretax, post-trans inc
Auten and Splinter (2019)					
2007	14.6%	14.0%	13.8%	13.4%	12.9%
2017	14.2%	13.5%	13.2%	12.8%	12.3%
2007-2017	-0.4%	-0.5%	-0.6%	-0.6%	-0.6%
BEA					
2007	15.3%	14.5%	14.2%	13.7%	13.3%
2017	16.8%	15.8%	15.4%	14.8%	14.2%
2007-2017	1.5%	1.3%	1.2%	1.0%	0.9%

Note: A&S estimates are only available through 2017.

Figure 1: Distribution of PI (2007-2018)

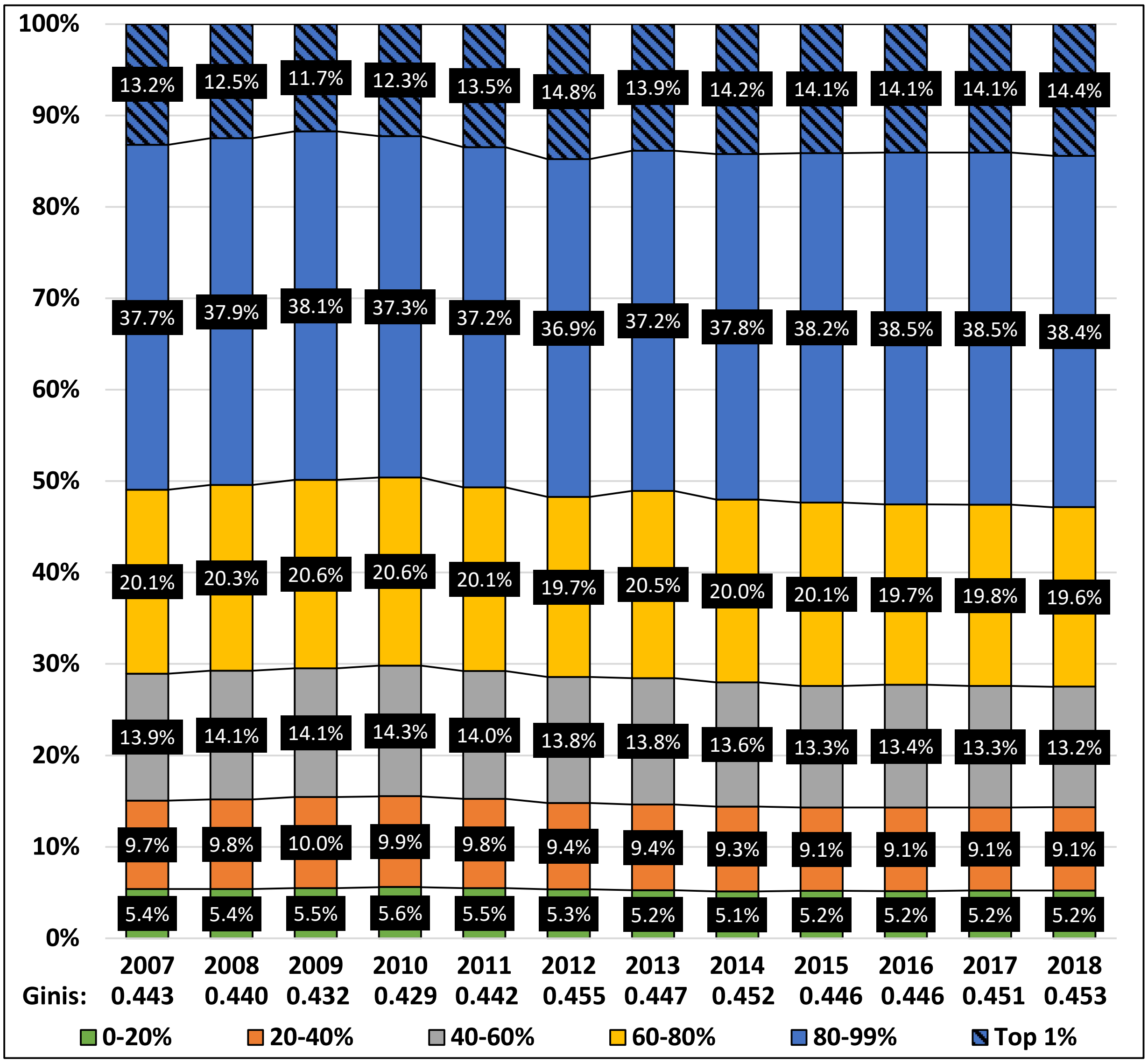


Figure 2: Composition of PI by Quantile (2018)

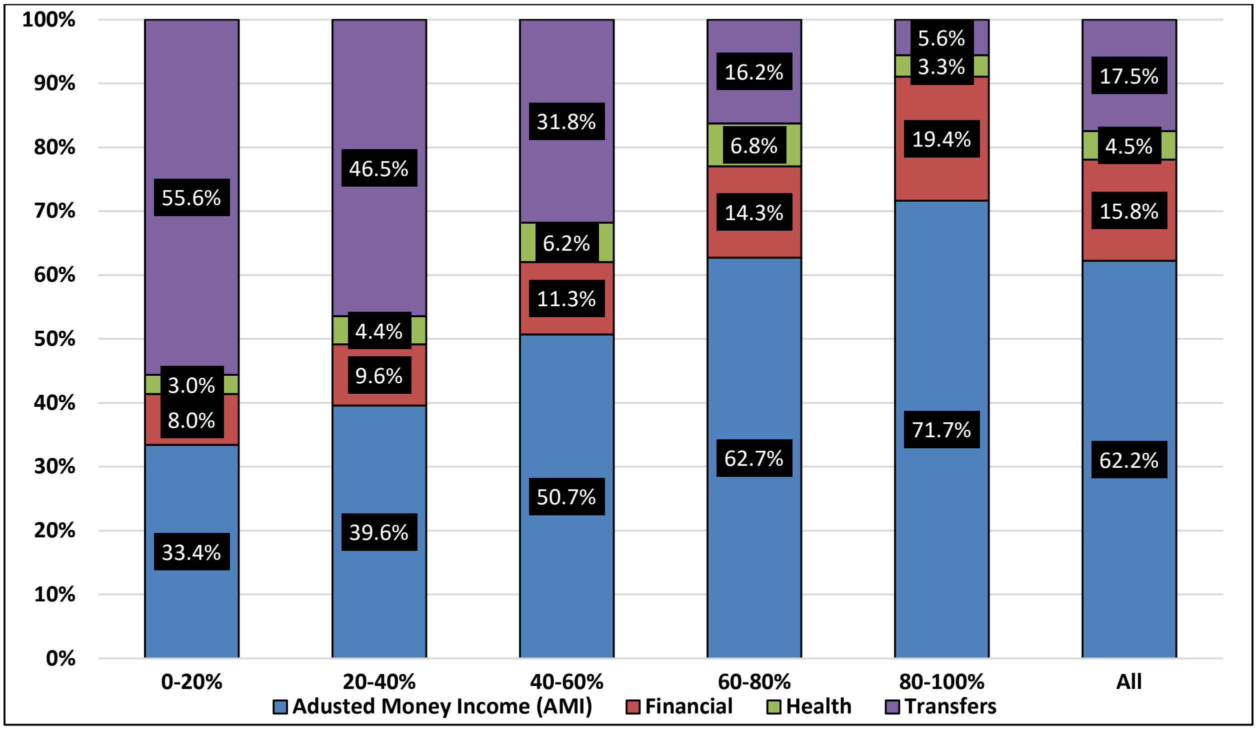


Figure 3: Transfers and Decile Shares of PI (2007 & 2018)

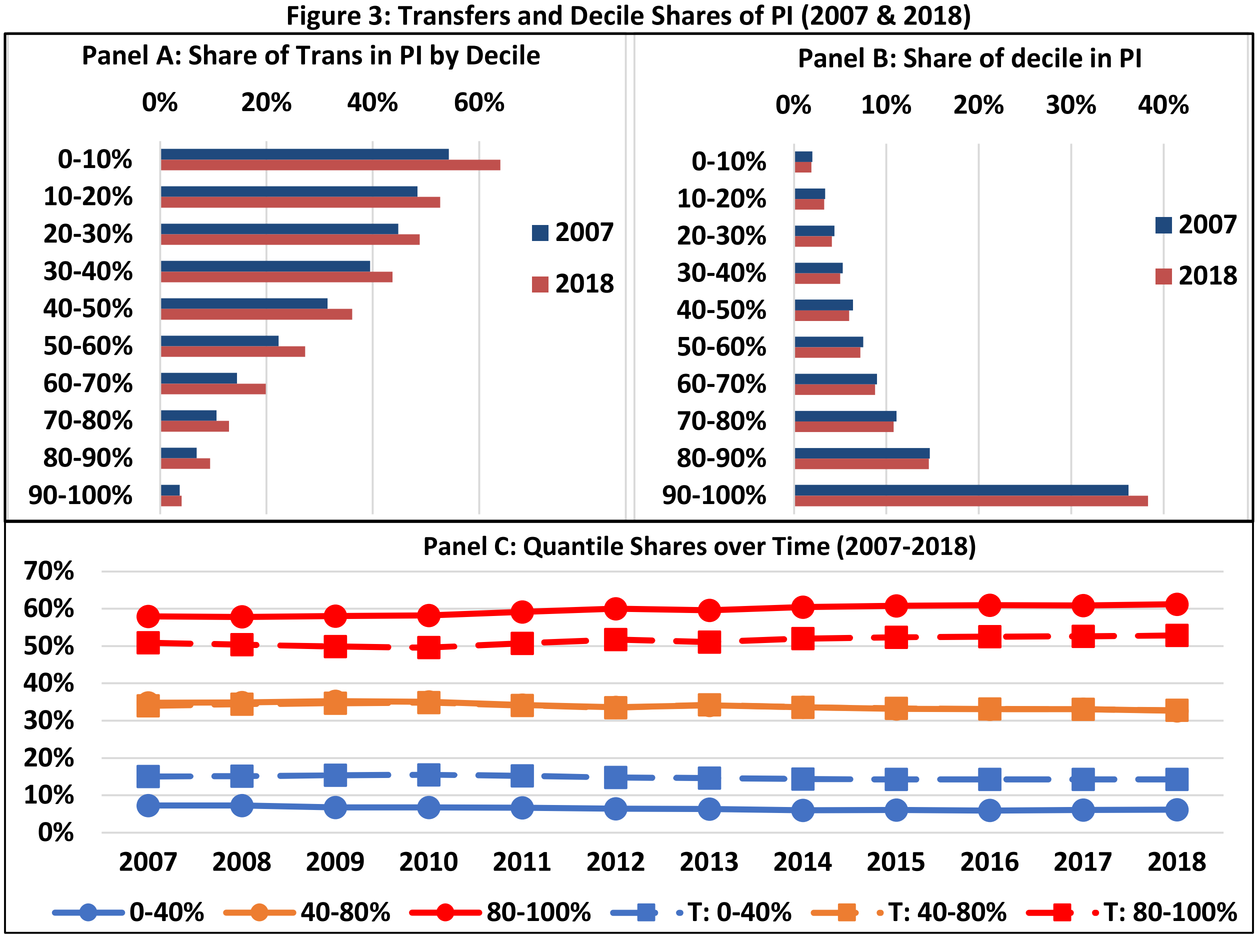


Figure 4: Income Distribution of PI with Iterative Addition of Transfers (2018)

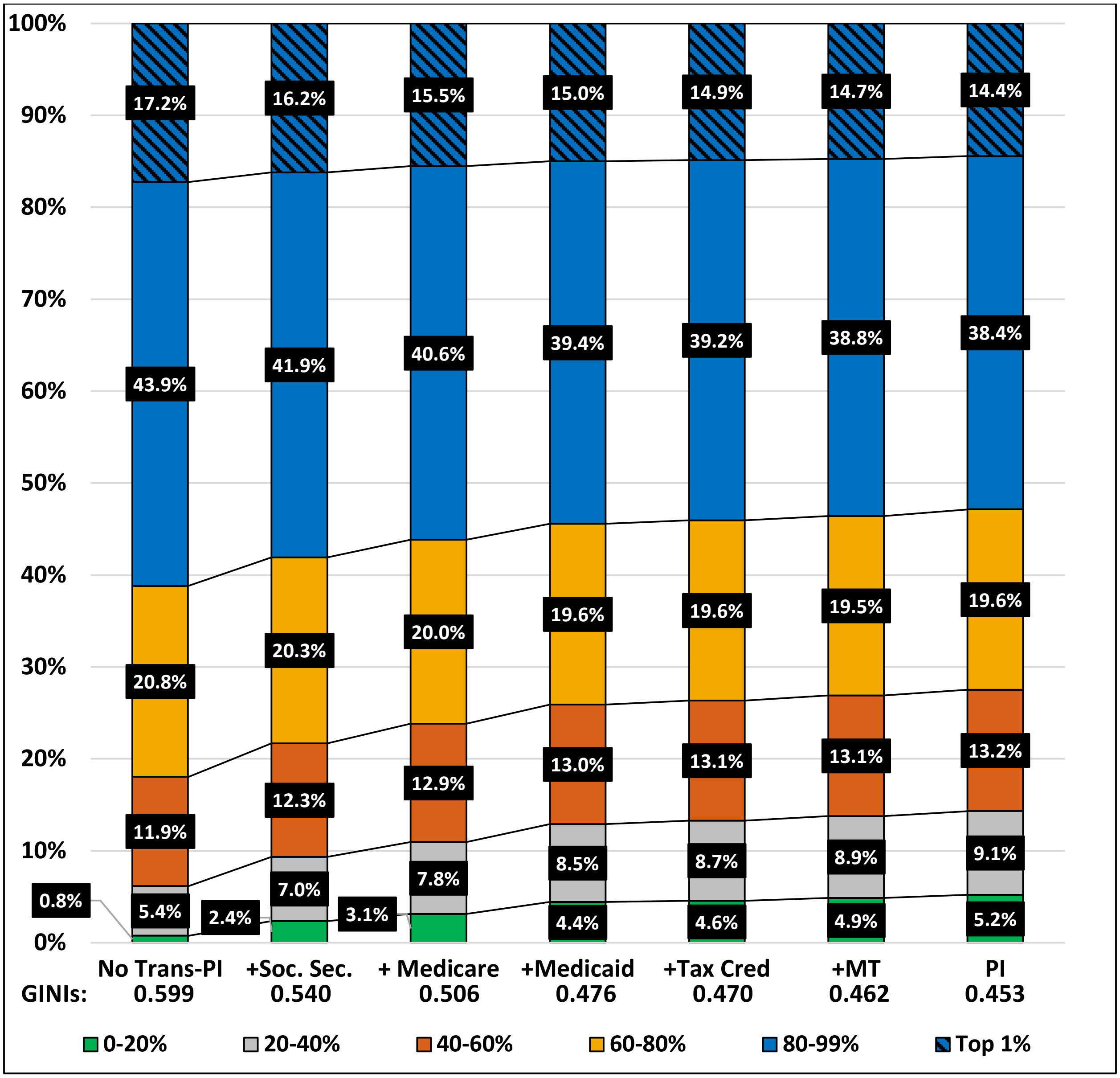


Figure 5: Share of Elderly Households (2007 & 2018)

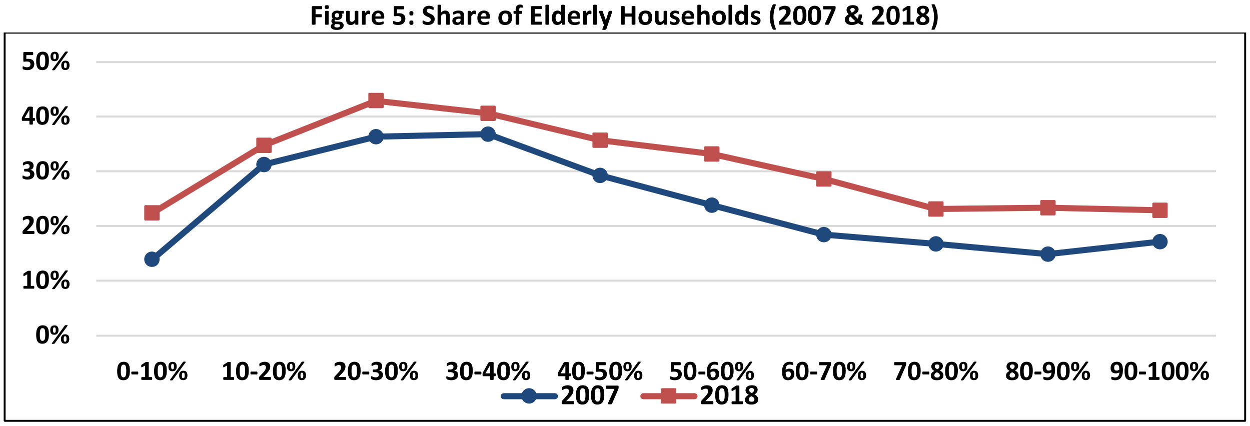
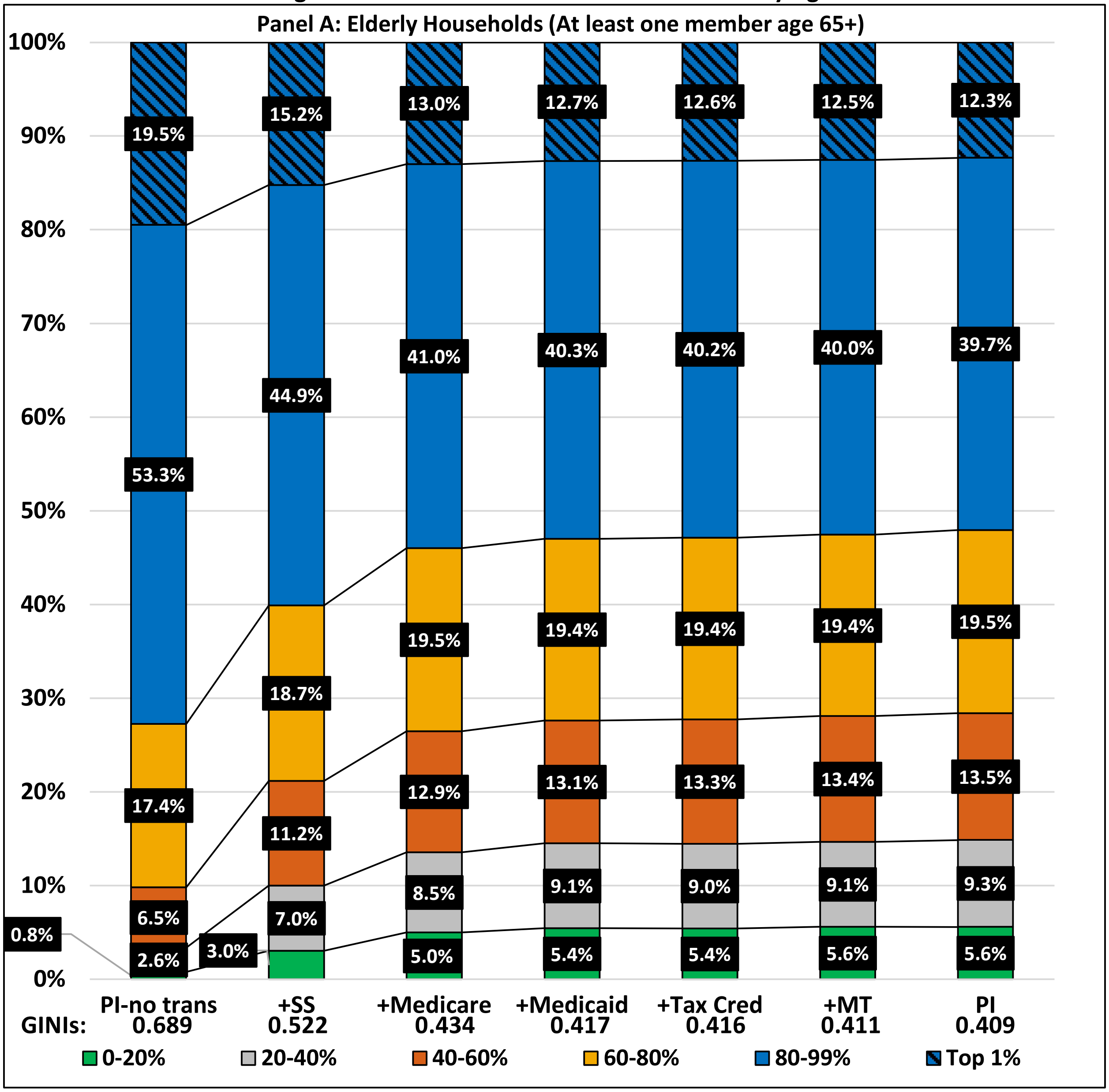
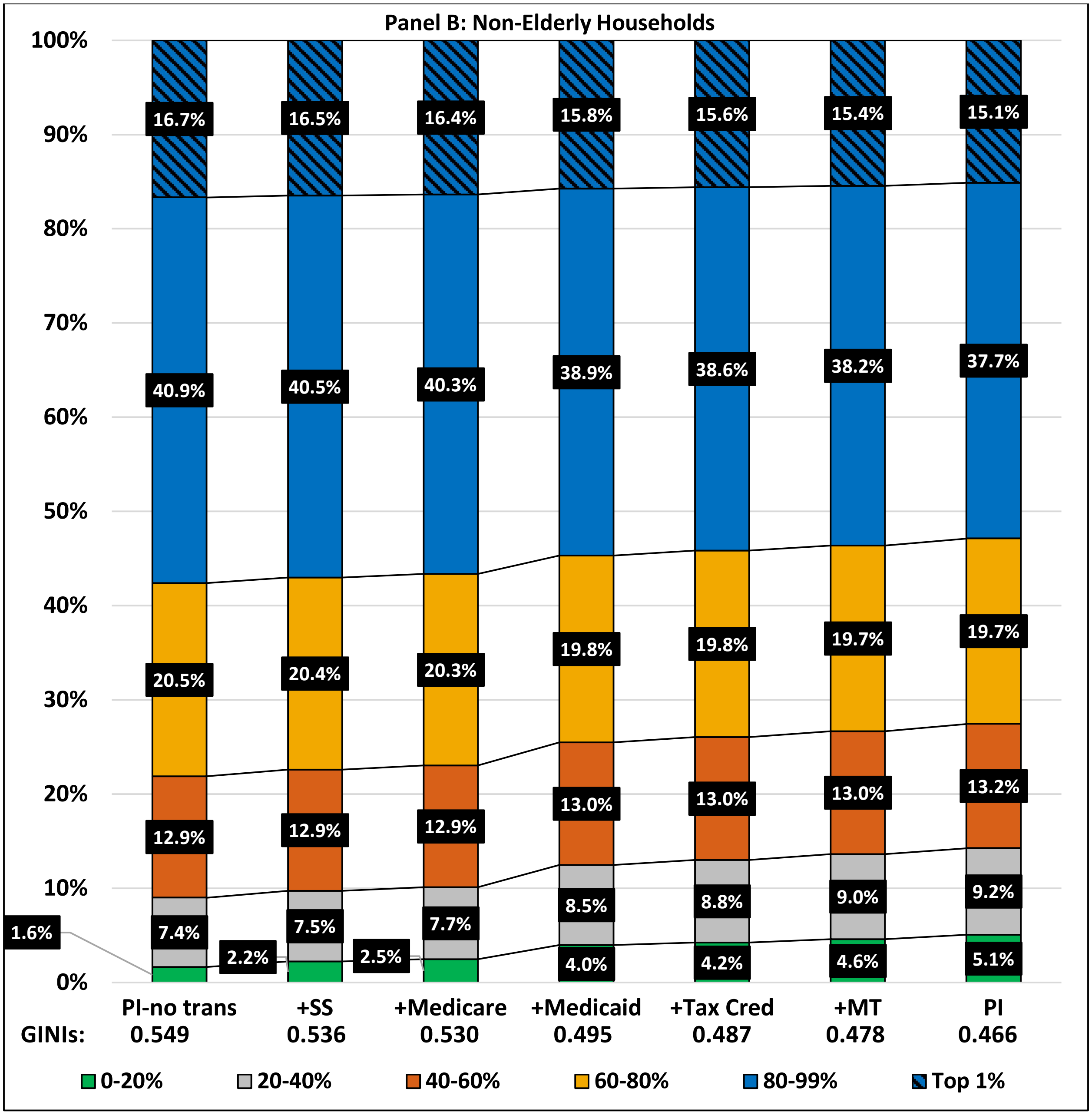


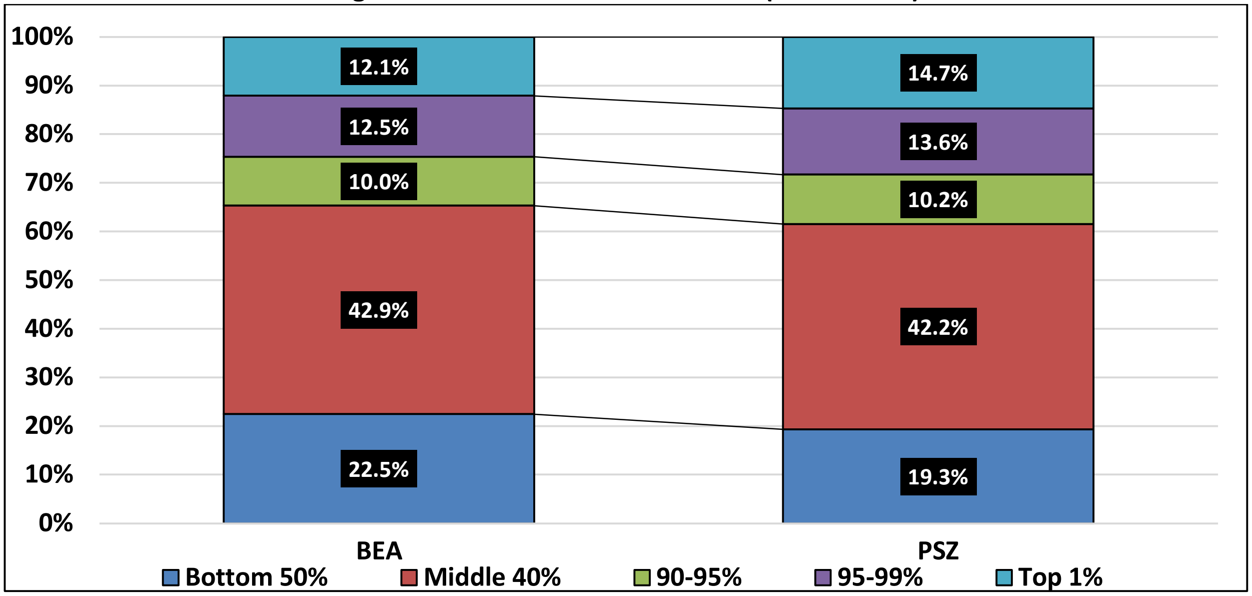
Figure 6: Iterative Addition of Transfers to PI by Age





Panel B: Non-Elderly Households
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
16.7%
16.5%
16.4%
15.8%
15.6%
15.4%
15.1%
40.9%
40.5%
40.3%
38.9%
38.6%
38.2%
37.7%
20.5%
20.4%
20.3%
19.8%
19.8%
19.7%
19.7%
12.9%
12.9%
12.9%
13.0%
13.0%
13.0%
13.2%
7.4%
7.5%
7.7%
8.5%
8.8%
9.0%
9.2%
1.6%
2.2%
2.5%
4.0%
4.2%
4.6%
5.1%
PI-no trans
+SS
+Medicare
+Medicaid
+Tax Cred
+MT
PI
GINIs:
0.549
0.536
0.530
0.495
0.487
0.478
0.466
0-20%
20-40%
40-60%
60-80%
80-99%
Top 1%

Figure 7: Role of Transfers for 2018 (BEA vs. PSZ)



Appendix Tables and Figures

Table A1: Distributional Effects of Medicaid Expansion for Non-Elderly Households

	Expanded Medicaid		Did Not Expand Medicaid	
	Δ Medicaid	Δ2007-2018	Δ Medicaid	Δ2007-2018
Mean PI	4.1%	17.7%	3.5%	15.5%
Median PI	6.0%	12.3%	6.0%	7.2%
0-20%	1.6%	-0.1%	1.4%	-0.4%
20-40%	0.8%	-0.6%	0.8%	-0.5%
40-60%	0.2%	-0.7%	0.1%	-1.0%
60-80%	-0.5%	-0.4%	-0.4%	-0.9%
80-100%	-2.1%	1.7%	-1.8%	2.9%
Top 1%	-0.6%	1.1%	-0.6%	4.1%
Top 5%	-1.1%	1.4%	-1.1%	4.3%
Gini index	-0.037	0.010	-0.030	0.040

Table A2: Shares of Transfers in pre-tax income (CBO vs. BEA)

	CBO				BEA			
	All	SS	Mcare	Mcaid & CHIP	All	SS	Mcare	Mcaid & CHIP
2007	15.2%	6.4%	3.9%	2.8%	18.1%	5.1%	3.8%	2.9%
2017	19.8%	8.0%	4.8%	4.8%	21.5%	5.9%	4.4%	3.7%
2007-2017	4.6%	1.6%	0.9%	2.0%	3.4%	0.8%	0.6%	0.8%

Figure A1: Distribution of DPI (2007-2018)

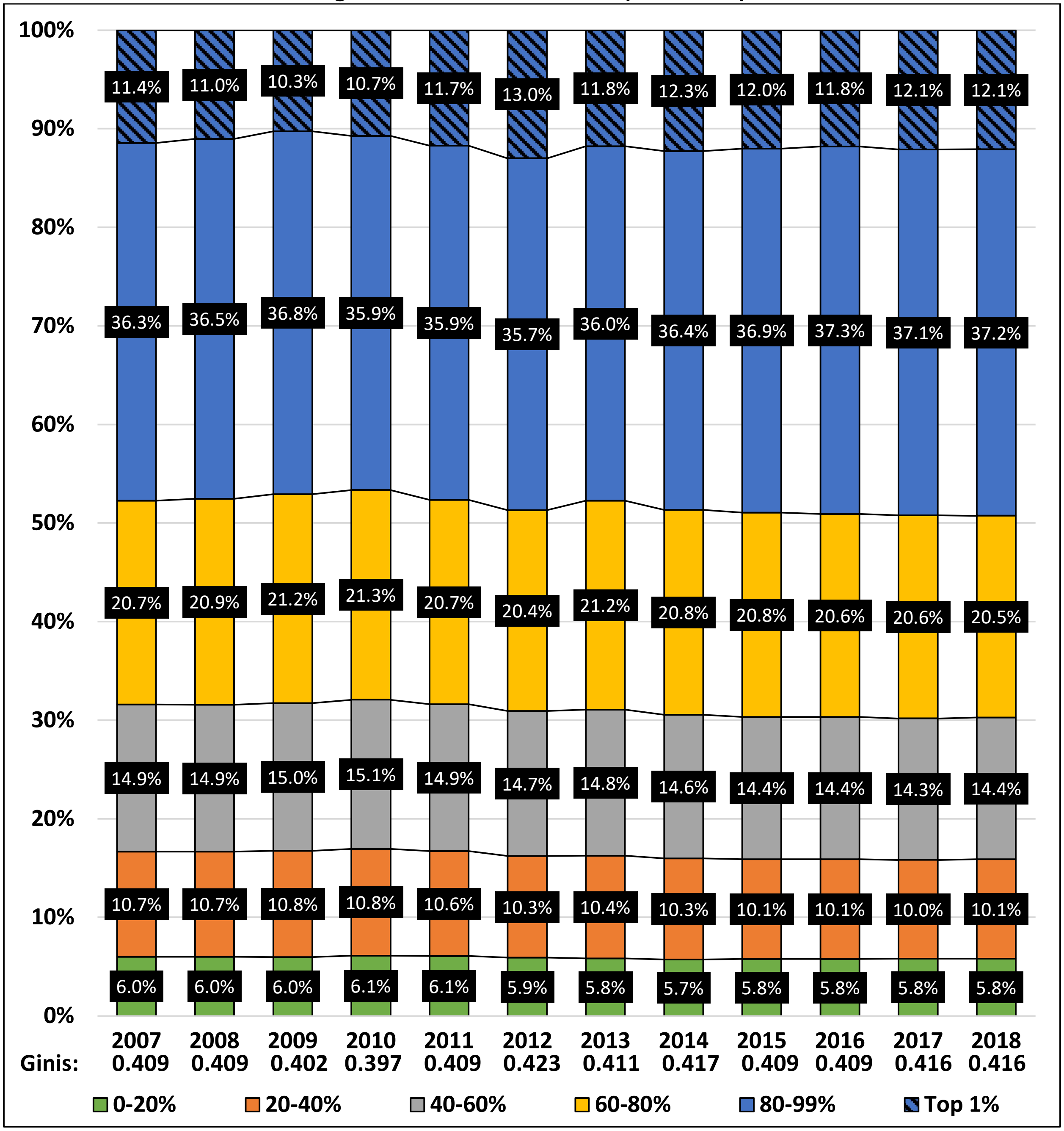


Figure A2: Iterative Addition of Transfers to DPI

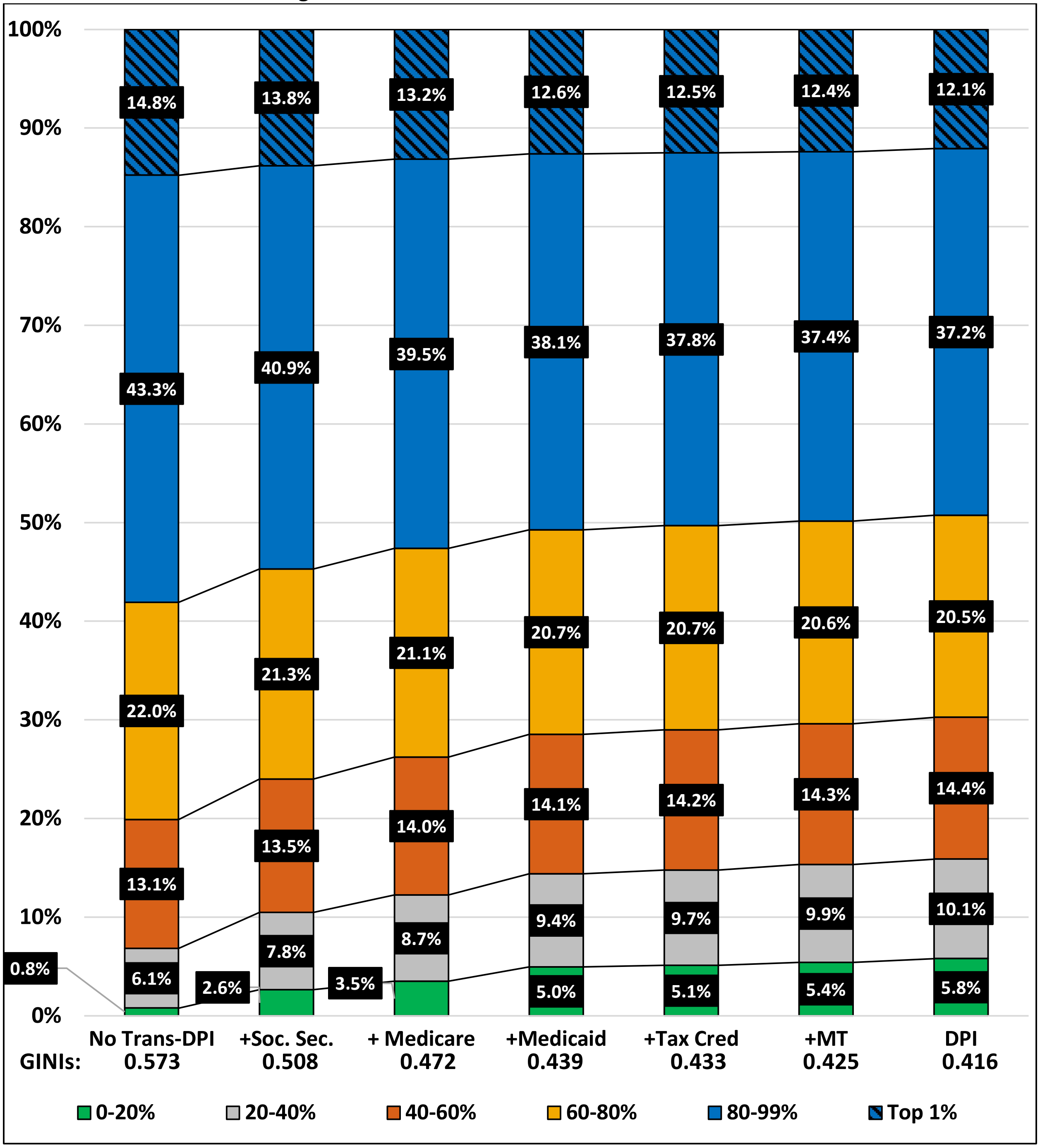


Figure A3: Comparison to PSZ – Transfer Decomposition by Quantile (2018)