Mult-No-More? The Migration Effects of Multnomah County's Preschool For All Income Tax *

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Abstract

This paper explores the migration and subsequent revenue effects of Preschool for All (PFA), a policy enacted in Multnomah County, Oregon that promised to provide universal, tuition-free preschool, funded by a new income tax on high income households. Multnomah County is home to Portland, the primary economic engine of Oregon, and it also shares a border with income-tax-free Washington state. Since local income taxes are relatively rare, this policy provides a unique opportunity to study the migration effects of a new income tax in a small geographic area of the US. Using two different sources of publicly available migration data, each with its own strengths and weaknesses, we take multiple empirical approaches to identifying potential causal impacts to migration into and out of Multnomah County, as well as across the Oregon state line. All analyses point to sizable, statistically significant increases in out-migration from Multnomah after PFA, especially among households likely subject to the tax. Substantial migration involved moving out of Oregon. Migration into Multnomah also declined, but the effects are less robust. Using these estimated migration effects, we calculate the impact of this migration on the tax revenue generated by PFA, as well as its overall impact on Oregon state income tax revenues, and find them to be nontrivial.

Keywords: local income tax, migration, tax competition, Tiebout sorting, synthetic difference-in-differences

JEL Codes: H71, H73, R23, J61

*The full replication file is available here: https://github.com/johniselin-econ/multnomah-county-tax. We'd like to thank Mark Skidmore and other participants at the Envisioning the Future of Local Government Finance for their helpful comments.

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1 Introduction

With the growing polarization of national politics and frustration over Congressional gridlock, state and local municipalities appear to be taking a more proactive stance towards policymaking. However, the policies of local governments (versus state or federal) seem likely to have stronger migration and thus revenue effects and, to the extent that they encourage residents to move across state lines, may have implications for state-level finances as well. A 2024 op-ed coauthored by the New York state comptroller warns of the accelerating decline in the state's population and, even more so, the state's income and tax base in recent years.[1] It further notes that it is high income taxpayers who are leaving and that the proportion of non-resident returns—those who do not live in New York but must pay tax on income earned there—has steadily increased. Both have outsized effects on the income tax base. It is notable that this article appeared well before the election of Zohran Mamdani as New York City mayor, whose platform included fare-free public buses, universal no-cost childcare and city-owned grocery stores, financed with increased taxes on the wealthy and corporations.[2]

The local policy we focus on here, Preschool for All (PFA), includes an income tax levied on high income residents in Multnomah County, Oregon beginning in 2021. Multnomah County includes Portland, Oregon, the primary economic engine of the state that sits on the border of income-tax-free Washington. This policy has caught the attention of Oregon's governor, Tina Kotek, who wrote in a June 2025 letter to the Multnomah County Chair:[3]

> "I am concerned that the program's current direction is not responsive to the economic realities of 2025. And if Portland does not rebound in the way we think it can, the downstream impacts on our economy will end up costing our

[1] See https://www.osc.ny.gov/press/releases/2024/03/dinapoli-and-heather-briccetti-mulligan-op-ed-nys-tax-base-dips-population.

[2] See `https://www.zohranfornyc.com/platform`.

[3] Governor Kotek's letter to County Chair Jessica Vega Pederson, dated June 10, 2025. Available at `https://apps.oregon.gov/oregon-newsroom/OR/GOV/Posts/Post/governor-kotek-issues-statement-on-multnomah-county-preschool-for-all`.

most vulnerable and lowest income Oregonians the most."

Kotek has been joined by other senior Oregon legislators in pressuring Multnomah County to revise its policy, leading to an ongoing debate in the state but little conclusive evidence as to its actual effects (Hou, 2025*a*).

Local governments are presumed to rely primarily on local property taxes, but localities are increasingly turning to income taxes. While these taxes are still not common, a recent study (Yushkov, 2025) shows they exist in 16 states and "constitute a significant share of local tax collections in six states" (p. 1020). A growing reliance on local income taxes revives and heightens concerns that such taxes drive away high-income taxpayers and thus shrink the tax base—as it is typically much easier to move out of a city or county than a state (Wilson, forthcoming). However, with the exception of the suggestive but inconclusive results from Yushkov (2025), little evidence exists about their possible effects on migration and, subsequently, tax revenues.

This paper helps close that gap by investigating the migration and revenue impacts of PFA, a policy initiative whose stated goal was to establish universal, tuition-free preschool in Multnomah County, Oregon. It includes a new income tax of 1.5% on taxable income over $125,000 (single) or $200,000 (joint), with an additional 1.5% on income over $250,000 (single) or $400,000 (joint), effective for individuals living or working in Multnomah County. Enacted in November 2020 via referendum (with 64% voting in favor) and becoming effective in January 2021, the policy is now the subject of much debate as critics, including Governor Kotek, contend it has driven away high-income taxpayers. Proponents of the policy argue that universal preschool attracts young families and point to an increased number of tax returns filed (Dean, 2025). Given that Multnomah County includes the major urban center of Portland, Oregon and is surrounded by several other counties that are a commutable distance, including some in the no-income-tax state of Washington, PFA appears to be an ideal setting and quasi-natural experiment to observe Tiebout sorting in response to a newly enacted tax-spending policy.

Our goal is to use the best, publicly available (and thus replicable) data and an exhaustive set of appropriate empirical techniques to investigate the impact of this policy on migration and state and local income tax revenues. We use two primary sources of data, each with its own strengths and weaknesses. The first is the Statistics of Income (SOI) IRS county-to-county flow data, which has the advantage of being based on nearly the entire universe of taxpayers and can identify where individuals are moving to and from for all U.S. counties. In addition to some well-documented errors in the mid-2010s (DeWaard et al., 2022), its primary disadvantage is its aggregate nature: county-to-county flows are presented without disaggregation by income, household structure, or any ability to observe individual-level characteristics.[4] Given the nature of this policy, certain groups (e.g., high income households, households with very young children) are likely to be more strongly affected; the IRS data is unable to investigate these differences. Additionally, the most recent year of data is tax year 2022, which means we can only observe two years of behavior after the policy is enacted.

These advantages and disadvantages are exactly reversed in our second source of data, the American Community Survey (ACS). The ACS has individual-level data and an extensive set of individual characteristics. It is also available through 2024, which allows us to study four years of post-policy behavior instead of only two. However, the ACS is based on a 1% sample of the total U.S. population, and, as such, the county of residence is suppressed for the majority of U.S. counties, including several of the smaller counties near Multnomah. In addition, the wording of the residence and migration survey questions combined with the year-round sampling likely introduces substantial measurement error (see, e.g., Conway and Rork, 2016).

Our empirical approach is to first apply econometric methods that are appropriate for both sources—Synthetic Difference-in-Differences (SDID)—so that we can make a head-to-head comparison of the results from these very different data sources. Finding similar results across the two sources lends credibility to each. We then apply empirical methods that are

[4]For a more detailed explanation of the data error, see Appendix Appendix B.

especially well-suited for each different source. Specifically, using the IRS flows we can report how the geographic patterns—where people are moving to and from—changed, and we can estimate traditional migration flow models, including flow fixed effects and time-varying location variables. Using the ACS, we can examine the conditional mean net-migration rates by key individual characteristics over time, and we can estimate individual-level, in- and out-migration DiD models, using households likely not subject to the policy as a control group.

Several confounding factors challenge our ability to attach a causal interpretation to the estimated effects. Foremost, the policy was enacted at the end of 2020, which means the timing of the policy shock coincided nearly perfectly with when the Covid-19 pandemic emerged. A second complication is that a few other policies emerged in the Portland area around the same time (discussed shortly), which could potentially influence migration—and in a similar direction. We perform an extensive list of robustness checks to address these concerns. Nonetheless, we acknowledge that our analysis cannot definitively establish causality, though the weight of the evidence across multiple approaches is strongly suggestive. We further note that the geography and policy environment of Multnomah, as well as the possible biases created by the confounding factors, likely make our estimates larger than what other local municipalities can expect if they enact a similar policy.

2 Background

In this section, we first briefly review what is known about local income taxes and about the possible effects of income taxation on migration more broadly. We then describe the specifics of the PFA as well as the general environment and possible confounding events in Multnomah County and the surrounding areas.

2.1 Past Research

Migration responses to income taxation have been widely studied, both in the U.S. and internationally (see Galle et al., 2025; Yushkov, 2025, for recent reviews). The general conclusion from these studies is that in many settings the migration effects are relatively modest such that they do not substantially offset the first-order revenue effects of the tax policy. These include studies of state-level "millionaire" taxes (e.g., Young and Varner, 2011; Young et al., 2016, although research on California's tax is more mixed; see Varner, Young and Prohofsky 2018; Rauh and Shyu 2024), estate taxes (e.g., Bakija and Slemrod, 2004) and income tax breaks targeting retirees (Conway and Rork, 2012; Iselin, Conway and Rork, 2025).

However, some evidence suggests that taxes on certain highly mobile groups or in smaller geographic areas do lead to larger migration and revenue impacts. Those mobile groups include billionaires (Moretti and Wilson, 2023) and possibly millionaires (as noted above), as well as star scientists (Kleven, Landais and Saez, 2013) and professional athletes (Akcigit, Baslandze and Stantcheva, 2016; Moretti and Wilson, 2017). Moreover, Galle et al. (2025) make the point that "money" may be more mobile than households, such that the stock of taxable income (roughly measured as adjusted gross income (AGI) in this setting) may be more affected, for example, than the number of tax returns.

Similarly, several studies of tax differentials in Europe, in particular the cantonal local governments of Switzerland, find stronger effects on migration (e.g., Schmidheiny and Slotwinski, 2018; Köthenbürger et al., 2025; Brülhart et al., 2022), which makes sense given their smaller geographic size. For instance, the median Swiss canton is about 1/100th the land mass size of the median U.S. state and has a population that is closer to a small, U.S. metro area. The most heavily populated Swiss canton (Zurich) has a population of approximately 1.6 million, which is about twice the size of Multnomah County's population and about two-thirds the size of the greater Portland metro area.

These findings suggest that taxing high income or otherwise highly mobile groups/incomes at a small geographic level, such as the county or city, is much more likely to trigger a reduction in net in-migration, with matching negative revenue effects. Yet, little is known about the effects of local income taxes in the U.S. In a recent paper, Yushkov (2025) provides an excellent history and overview of local income taxes in the U.S. and then analyzes the effects on migration of changes in the county-level taxes in Indiana and Maryland between 2011 and 2021. The study uses the same IRS flow data as we do and takes a stacked difference-in-differences approach, with numerous robustness checks. All study counties had a tax in 2011 and so the changes only apply to the rate; while fairly numerous (190 changes across the two states), most were quite small with an average of 0.25 percentage points. The overall conclusion is that “major increases in local income tax rates have a negative, although in most cases insignificant, effect on both migration inflows and migration outflows” (Yushkov, 2025, p. 1018). These results are thus inconclusive; while a modest, negative effect on inflows is expected and consistent with past work, the effect on outflows is unexpected.

Another recent paper by Cassidy, Dincecco and Troiano (2024) investigates the adoption of state income taxes over 100+ years and finds that post-World War II adoptions led middle- and higher-income households to move to non-income-tax states and, as a result, the long-run level of tax revenue generated did not increase. It seems possible that the adoption of a new tax may have stronger effects on migration than a change in rate, another distinguishing feature of our study.

We provide additional details on the policy as well as the general economic and policy environment in the next subsection (2.2). Here, however, we note that one of the Portland City Councilors, Mitch Green, has produced an analysis of the PFA (Dean, 2025). This descriptive analysis also uses the IRS migration flows for Multnomah and the 6 counties in the Portland MSA. It acknowledges “a large upward trend in the average Adjusted Gross Income (AGI) of households leaving Multnomah County during the pandemic years” (Dean, 2025, p. 1) but makes several counter-arguments to drawing a detrimental conclusion. Those include the possible outsized influence of a very small number of very high-income households (which could skew average AGI) and the fact that individuals who leave Multnomah County may still be subject to the tax if they earn income there. Our analysis, which uses individual-level data from the ACS as well as the IRS flows, provides additional descriptive evidence. More importantly, it applies causal inference methods and a rigorous, multi-pronged empirical approach to isolate the likely causal impacts of the policy on migration, at both the county and state level.

2.2 A Primer on Multnomah County, the Portland Area, and Preschool for All

Multnomah County is Oregon's smallest county in terms of landmass and its largest in terms of population, estimated to be 795,000 in 2024. This is down from 815,000 in 2020. As shown in Figure 1, Multnomah County is home to Portland, the state's largest city by population, and it borders two counties, Clark and Skamania, in Washington state. Seventy-five percent of Multnomah's population lives in Portland, with the remaining 25% spread among 9 smaller cities in the county.

The city of Portland is part of the Portland-Vancouver-Hillsboro metropolitan statistical area. It consists of 5 counties in Oregon (Multnomah, Washington, Clackamas, Yamhill, and Columbia) along with Clark and Skamania counties in Washington state. The MSA population is estimated to be over 2.5 million people in 2025 and, unlike Portland, its population has grown slightly (2.53M in 2025 vs. 2.51M in 2020).[5] While Marion County, home to the state capital Salem, is not part of the Portland MSA, many state workers live in Portland and commute the hour to Salem.

There are three levels of local government in this area—city, county, and a third layer of government known as Metro. Metro is the only directly elected regional government in the U.S. and is responsible for overseeing general land use and regional transportation

[5]See Portland-Vancouver-Hillsboro, OR-WA Metro Area, https://censusreporter.org/profiles/31000US38900-portland-vancouver-hillsboro-or-wa-metro-area/.

planning. Shown with a purple dotted outline in Figure 1 (inset), it covers 24 cities in Clackamas, Multnomah, and Washington County, along with the unincorporated parts of those counties.

Prior to 2021, there were no local income taxes in any municipality in Oregon (or Washington or California).[6] Residents faced only the Oregon personal income tax, which is a graduated tax with a top marginal tax rate of 9.9% on households with income above \$125K/\$250K (single/married) since 2012. Thus, even before PFA, residents could avoid paying the Oregon state tax if they moved to nearby Clark or Skamania counties in Washington. This underscores the need to explore the change in migration patterns and account for the presence of pre-existing trends.

During 2020, two new local income taxes were passed. The first is Preschool for All (PFA), which is the main focus of debate and this project. It was passed by voters in November 2020 (effective January 1, 2021) with the stated goal of establishing a tuition-free preschool program within Multnomah County. It imposed a personal income tax of 1.5% on taxable income above \$125K/\$200K (single/joint), with an additional 1.5% above \$250K/\$400K. In 2027, the rate is scheduled to increase by 0.8 percentage points (leading to marginal tax rates of 2.3% and 3.8%).

Residents of the county have 100% of their Oregon Taxable Income subject to the tax, whereas non-residents have their income sourced in Multnomah subject to the tax. The taxing of non-resident Multnomah-earned income may help discourage tax-induced migration for those households who are in the Portland labor force, as any effort to avoid the tax would require changing both their residency and place of work. This feature is one reason why we might suspect high income retirees to be more likely to move out of Multnomah. There is also no indexing for inflation. This can help explain why the number of returns filed have increased, a fact used to argue in favor of PFA (Dean, 2025; Hou, 2025*b*), even as the population appears to be declining. In 2022, the tax generated \$187 million in revenues, and

[6] The TriMet payroll tax, paid by employers, has existed since the 1970s but is not a personal income tax. See https://trimet.org/taxinfo/.

there are currently excess funds of $485 million that have not yet been spent.[7] This excess is in part due to the county failing to expand preschool as quickly and broadly as proposed (Hou, 2025*b*).

The second tax was the Metro supportive housing services tax, approved by voters in May 2020 (also effective January 1, 2021) to fund services for people experiencing or at risk of homelessness.[8] This is a 1% tax that kicks in for income above $125K/$200K. The thresholds are indexed for inflation starting in 2026. It is set to expire in 2030, and is paid by residents of Multnomah, Clackamas, and Washington counties or by non-residents on their sourced income within Metro's jurisdiction.

These three different income tax systems lead high income taxpayers in bordering areas to face very different tax rates. Table 1 provides key characteristics, including the taxes faced by different household income levels, in the seven counties in the Portland MSA plus Marion County. These eight counties are grouped into four categories: (1) Multnomah (faces all 3 taxes), (2) Washington and Clackamas (face Metro and state), (3) Marion, Yamhill, and Columbia (face only state), and (4) Clark and Skamania (face no tax). This table shows that high income residents living in Oregon face substantial marginal tax rates that can be a couple percentage points higher depending on their Oregon county and that would be zero if they moved to Washington. Wilson's (forthcoming) finding of a resistance to moving across state lines underscores the potential of this inter-county difference to have an effect.

PFA and the new Metro housing services tax were not the only changes in policy during this time, however. City of Portland voters approved local measure 26-215 the same year (2020), which authorized the district to issue $1.2 billion in bonds to fund school renovations. This measure did not increase the existing property tax of $250 per $100K of assessed value. Also in 2020, at the state level Oregon voters approved Measure 110, which decriminalized personal possession of small amounts of hard drugs. By making it a civic violation, Measure

[7]See Multnomah County Auditor's Office, *Financial Condition Report 2024*, https://multco.us/info/financial-condition-report-2024.

[8]See Metro, *Supportive Housing Services*, https://www.oregonmetro.gov/what-metro-does/housing-and-homelessness/supportive-housing-services.

110 was meant to focus on treatment. But due to a lack of resources and growing complaints of increased public drug use, its decriminalization provisions were partially reversed by HB4002 in 2024, which recriminalized drug possession while retaining the treatment-funding components. While this measure applied statewide and a similar measure occurred in Washington, it likely had the strongest impact on the urban areas, especially Portland.

A few other events occurred that could have affected the desirability of Portland and Multnomah County during this time period. The Portland Public Schools had a strike that lasted from November 1–26, 2023, which combined with the aftereffects of shutdowns due to the Covid-19 pandemic, has led to a gradual decline in enrollment numbers as more families leave the system (Miller, 2025). There were also the 100 days of protest after the killing of George Floyd in the summer of 2020, which led parts of downtown Portland to be boarded up for over a year and has been blamed for its slower rebound post-Covid (Rott, 2020). Finally, there were multiple, historic wildfires across the state over Labor Day weekend in 2020 that caused significant damage to rural parts of Marion and Clackamas counties and impacted air quality throughout the Portland metro.

The bottom line is that while we do our best to isolate the causal impacts of PFA on migration behavior, we must acknowledge there were other policies and events at play as well, many of which may have contributed to residents' decision to leave the area. This is another reason why we see our estimated effects as an upper bound on the effects of PFA.

3 Data Description

We use two sources of publicly available data on county-level migration: the annual county-to-county migration flows from the Internal Revenue Service (IRS) Statistics of Income (SOI) division, henceforth referred to as the IRS data, and individual-level data on residence and migration, as well as several other characteristics, from the American Community Survey (ACS). Both the one academic study of local income taxes, to our knowledge, (Yushkov,

2025) and the analysis of PFA conducted by Portland City Councilor Mitch Green's office (Dean, 2025) use the IRS data in measuring migration. More broadly, both of these sources have been used extensively for the study of inter-county migration and have distinct benefits and disadvantages, discussed in more detail below.

The IRS SOI division produces annual estimates of both county-level characteristics and county-to-county migration flows using data on the universe of tax returns. This is a part of a larger effort by the IRS to provide information across different levels of geography, including the state, county, metropolitan area, congressional district, and zip code.[9] We use migration data starting with tax year 2016 (representing the 2015–2016 flows) through 2022 (representing 2021–2022 flows). These migration statistics are based on 9-digit zip codes reported on tax returns, processed using a U.S. Census Bureau zip-to-county crosswalk. The files are limited to individuals who filed taxes in two subsequent tax years, with a non-missing zip code in each year. There are several other constraints, including timely filing, not being claimed as a dependent, and cleaning related to fraudulent returns.

The migration data shows county-to-county flows of returns (i.e., taxpayer units, so approximately households), exemptions (i.e., individuals), and Adjusted Gross Income (AGI). AGI is especially helpful both because it is the IRS measure of migration that best accounts for income differences, and because it captures that "money moves" (in addition to people) noted by Galle et al. (2025). It is also the most helpful measure in calculating tax revenue effects.

Our second source of migration statistics, the ACS, is a large-scale survey conducted by the U.S. Census Bureau annually. The ACS is designed as a 1% sample of the U.S. population, and it asks a range of questions regarding individual and household demographic and economic characteristics. Importantly, the survey contains information on migration,

[9]These efforts are subject to a range of data privacy restrictions, in order to limit the possibility that individual taxpayer characteristics are revealed by the release of the aggregate statistics. For example, at the county level, AGI groups within a given county with fewer than 20 returns are either combined with another AGI group, and counties with fewer than 20 returns for any given income or tax item have that item suppressed.

asking where a given individual lived one year prior to the interview. The most recent year available is 2024, which allows us to observe migration between 2023 and 2024.

As noted in the introduction, these two datasets are nearly perfect complements to each other, as they have opposite advantages and disadvantages. These qualities are summarized at the top of Figure 2. The main benefits to the IRS data are its near-universal coverage of individuals and counties (conditional on tax filing), its unambiguous definition of residence (the address of the tax return), and its measure of the income that "is moving," AGI. In particular, observing where the tax return is filed and the AGI associated with it is extremely helpful in calculating the possible tax revenue effects of PFA. Its main limitation is that it contains no individual or household-level characteristics (i.e., the unit of observation is the county pair) and it is only available through 2022, only two years after PFA. The IRS data has other, less impactful limitations as well.[10]

The main benefits of the ACS are that it contains individual-level data, such that we can identify specific households that are likely more or less affected by PFA, facilitating a difference-in-differences approach, and it is available through 2024, giving us 4 years to study after PFA is enacted. The biggest disadvantage is that it is only based on a 1% sample, which leads to a relatively small number of observed individuals/moves in each county. This small number creates measurement error and, even more problematic, leads to many of the county identifiers being suppressed. For example, while the IRS identifies the flow of returns, exemptions, and AGI between all U.S. counties, the ACS is only available for 389 counties. Unfortunately, several of the counties surrounding Multnomah are too small to be identified.

Another problem is the way that residence is defined and measured in the ACS (see Conway and Rork, 2016; Van Auken et al., 2006, for more detailed discussion). Briefly, the ACS defines location as where one now resides and has lived—or will live—for at least two

[10] First noted by DeWaard et al. (2022), there is a notable degree of noise in the public migration data released by the IRS during the 2014–2017 period. There are apparent moves that are either not real or whose timing is incorrectly recorded. As long as the error is randomly distributed across counties, the error will introduce noise into the pre-period but will not bias our estimates. We explore this in Appendix Appendix B, and find that Multnomah County is not an outlier in terms of the data anomaly at the county level.

months. Especially because of the ACS's year-round sampling, this "residence" may capture seasonal or otherwise temporary residents. The respondent is then asked where they lived 1 year ago. A difference in locations is inferred to be migration but can therefore also capture extended temporary moves (such as "snowbirds"). There is also no guarantee that it is the location where they will file their taxes.

There are alternative data sources that have been used to measure migration, including other government surveys like the Current Population Survey (CPS) or private datasets like moving van data (see Conway and Rork, 2022). However, these face a range of problems, like small sample sizes in most surveys (see Conway and Rork, 2016), and issues with representativeness and availability for private datasets. The ideal data for this project would be the confidential IRS records, as they contain information on individual tax returns connected over time; this is the data underlying the IRS flow data and used in our related study of elderly interstate migration (Iselin, Conway and Rork, 2025). However, we do not have access to these restricted data for this project at the current time and, even if we did, our results could not be easily replicated or explored more extensively by others.

3.1 Different Measures of Migration

Migration is measured in two dimensions, origin i and destination j, over a period of time t, and at its most granular level is measured at the individual level, h. It is this level that is observed in the ACS, albeit for only 1% of the population. Were it more widely available, it would be the ideal unit of observation for estimating a random utility, location choice model (McFadden, 1978). However, with the small number of relevant locations actually observed in the ACS data, we instead turn to more aggregate measures:

1. *Individual-level in-(out-)migrants*, M_{hit}: a dummy variable equaling 1 if individual h moved into (out of) county i during period t. Non-movers ("stayers") are included and assigned a zero. This measure can be observed for the 389 counties available in the ACS and can be used to estimate in-migration (pull factors) and out-migration (push

factors) behavior in separate models.

2. *County-pair flows*, M_{ijt}: the number of individuals (or tax units, or AGI) who moved from county i to county j (assuming both are observed) during t. In principle, this flow measure could be constructed for different types of individuals using the ACS; however, the limited number of counties available lead us to only use the flows from the IRS for returns, exemptions, and AGI.

3. *County migration rates*, M_{it}: the number of people moving into (out of) county i divided by county i's population, defined as the in-migration rate (out-migration rate). Subtracting out-migration from in-migration provides the net in-migration rate, which captures the impact that migration is having on the county's population and tax base. These rates could be further separated by demographic characteristic (e.g., college-educated, etc.) using the ACS or by returns, exemptions, or AGI using the IRS.

These measures are summarized in the bottom panel of Figure 2 and are the main measures we use in our different empirical strategies, described in Section 4. Note that the county migration rates can be calculated for both the ACS and the IRS migration measures. Using the counts of individuals (exemptions), households (returns), and the sum of total household income (AGI), we can create ACS and IRS migration rates that are directly comparable and can be estimated with the same empirical approach (SDID). As we describe in detail in the next section, we therefore begin by investigating those directly comparable measures before then investigating each data source's more granular measures.

3.2 Other Variables

To control for county-level, time-varying demographic or economic characteristics in our models, we use information from a range of government or academic sources. First, we pull information on county-level population counts and income, with which we calculate per capita income, from the Bureau of Economic Analysis's County and MSA Personal Income

Summary file (CAINC1). These data are available through 2023, and we linearly project the statistics county-by-county for 2024. Second, we obtain county-level unemployment rates from the Bureau of Labor Statistics' Local Area Unemployment Statistics, which we aggregate from the monthly to the annual level. We also use data from the ACS to calculate the median property tax paid in each county; recall that this variable is only available for a small subset of counties observed in the IRS flow data (389 out of 2,718 counties). We estimate our models both with and without these controls. We utilize data from the *New York Times*' archived Covid-19 data tracker that includes county-level estimates of cases and deaths from 2020 through 2023. We use these data, combined with a k-means clustering approach, to match Multnomah County to a set of other counties with similar trajectories of Covid-19 severity in creating one of the donor pools for the SDID analyses.

Finally, we employ data from the Johns Hopkins Initiative on Innovative Governance (JII) stringency index, which measures the duration and intensity of Covid-19 policy restrictions (e.g., stay-at-home orders, business closures, mask mandates) at the county level. This provides a complementary approach to controlling for the pandemic: while the Covid cases/deaths matching captures the *severity* of the health crisis, the stringency matching captures the *policy response*, which may be more directly relevant to migration decisions. We use the JII stringency data to construct an additional donor pool via k-means clustering on the duration of restrictions, producing the "stringency-matched" sample of control counties that appears in our highlighted benchmark set.

4 Empirical Strategy

Our overarching approach is to begin by applying the same empirical methodologies to the two different sources of migration data (ACS and IRS) so that we can explore the effects of their strengths and weaknesses. Finding similar results across the two provides some justification and reassurance in subsequently taking a more tailored empirical approach to each one. Figure 3 summarizes our overall approach and the specific empirical models estimated.

4.1 Synthetic Difference-in-Differences Applied to Both Data Sources

We can construct county-level in-, out-, and net-migration rates, calculated in terms of households (returns), individuals (exemptions), and income (AGI), for the ACS (IRS) in every year and county available for each source. In addition to comparing the descriptive statistics for these measures, we could take a difference-in-differences approach to estimating the effects of the PFA:

$$Y_{it} = \alpha + \beta \left(\text{Post}_t \times \text{Multnomah}_i\right) + \gamma_i + \delta_t + \mathbf{X}_{it}'\boldsymbol{\theta} + \varepsilon_{it}, \tag{1}$$

where Post_t is an indicator equal to one if the observation is in or after 2021, Multnomah_i is an indicator equal to one if the county in question is Multnomah County, γ_i and δ_t are county and year fixed effects, and $\mathbf{X}_{it}$ is a vector of time-varying county-level controls.

If we assume that most households do not benefit from the universal preschool aspect, standard location choice theory would predict that the coefficient β would be positive for out-migration (i.e., causes people to move out) and negative for both in- and net in-migration. We can test for parallel trends and dynamic effects by estimating the event-study extension of this equation:

$$Y_{it} = \alpha + \sum_{k \neq 2019} \beta_k \left(\mathbf{1}[\text{Year}_t = k] \times \text{Multnomah}_i\right) + \gamma_i + \delta_t + \mathbf{X}_{it}'\boldsymbol{\theta} + \varepsilon_{it}. \tag{2}$$

A major complication, however, is that there is only one treated county, Multnomah. We therefore estimate these models using Synthetic Difference-in-Differences (SDID), a variant of synthetic control analysis. Arkhangelsky et al. (2021) combined elements of both difference-in-differences and Synthetic Control Method (SCM) approaches to create the SDID approach.

The two key features are the re-weighting of control (donor) units to create a synthetic version of a treated unit (or units) that serves as a counterfactual, and the allowance of a level shift between the treated and synthetic control unit. The method therefore borrows beneficial features from both SCM and DiD approaches and is well suited to cases where there is one treated unit. Inference in this setting (i.e., with one treated unit) is done via a placebo approach, where a treatment effect is estimated for each untreated observation (county in this setting), and the distribution of effects is used to evaluate the probability that the actual treatment effect is abnormal. For more information, see Arkhangelsky et al. (2021) and Clarke et al. (2024), which details the Stata implementation of this estimator.

A key decision in any methodology that builds off the intuition of SCM is what set of control/donor counties will be used to construct the synthetic treated unit. In this case, we first restrict the sample in all cases to exclude Alaska and Hawaii, and second remove California, Washington, and the remaining counties in Oregon. The first restriction is due to the non-representative nature of the two non-contiguous states. The second is to avoid any spillover effect of Multnomah County migration on the donor pool: most migration to and from Multnomah is on the West Coast, and we want to use a set of control counties whose in- or out-migration rates are not impacted by the policy change. We are then left with the pool of counties in both datasets in the 45 states (plus DC) that we observe in all years. This is our first sample pool ("all counties"), and we further restrict it in several ways to construct four additional donor pools:

1. *Urban (top 5%)*: restricted to the top 5% of counties by urbanization rate (using 2020 decennial census estimates), focusing on a more comparable pool of counties in terms of socioeconomic characteristics.

2. *Urban-Covid*: the subset of urban counties (top 25%) that had a similar pattern of Covid-19 deaths and cases between 2020 and 2023 as Multnomah County, using k-means clustering on case and death trajectories.

3. *Demographic match*: counties matched to Multnomah on a vector of pre-treatment demographic characteristics (population, income, education, age distribution).

4. *Stringency match*: urban counties (top 25%) matched on the duration of Covid-19 policy restrictions using the JII stringency index (see Section 3.2). This donor pool captures the policy response to the pandemic—which may be more directly relevant to migration decisions—rather than the health outcomes themselves.

We report results for all five donor pools in the specification curves. Throughout the paper, we highlight four SDID benchmark specifications formed by crossing the two main data sources (IRS and ACS college) with the two main donor pools (all counties and stringency-matched). Table A4 in the Appendix reports the number of donor counties in each pool.

4.2 A Deeper Analysis of Each Source

We then explore the more granular, but not comparable, migration measures available in each source. The IRS flow data can show us the geographic patterns of migration—what counties people in Multnomah are moving to (and how much) and what counties new migrants to Multnomah are coming from—before and after PFA. Our more refined approach to the IRS data is summarized in the left-hand box in Figure 3.

We provide descriptive evidence with a series of maps. To attempt to identify a causal effect of PFA, we estimate a PPML model of county-to-county migration flows with M_{ijt} as the outcome variable:

$$M_{ijt} = \exp\big(\beta_1 \,\text{OutPost}_{it} + \beta_2 \,\text{InPost}_{jt} + \mathbf{X}'_{it}\boldsymbol{\theta}_O + \mathbf{X}'_{jt}\boldsymbol{\theta}_D + \gamma_{ij} + \delta_t\big) \times \eta_{ijt}, \tag{3}$$

where $\text{OutPost}_{it} = \mathbf{1}[i = \text{Multnomah}] \times \text{Post}_t$ and $\text{InPost}_{jt} = \mathbf{1}[j = \text{Multnomah}] \times \text{Post}_t$.

The key coefficients of interest are β_1 and β_2, which capture the effect of PFA on the decision to move out of Multnomah (and thus presumed to be positive) or into Multnomah (presumed negative). In estimating the effects of PFA, this model controls for unobserved characteristics common to each flow, such as whether they share a border, cross a state line (a key feature explored by Wilson forthcoming), and longtime established migration patterns, as well as the distance between the two. Including $\mathbf{X}_{it}$ and $\mathbf{X}_{jt}$ further controls for any time-varying, county-specific factors, such as property taxes or the unemployment rate. As in the SDID, we also estimate a full event-study version of the model. We utilize a PPML approach due to the prevalence of flows with no movers in a given year and the need to include multiple fixed effects (see Chen and Roth, 2024, for more information).

In contrast, the ACS data can show us *who* appears to be doing the moving, before and after PFA. We expect the tax aspect of the PFA to mostly affect higher income/more educated households and the preschool aspect to mostly affect younger households, especially those with very young children. Our approach to the ACS is summarized in the right-hand box of Figure 3. Here too, we start by providing descriptive evidence; controlling for all other characteristics, we calculate the conditional mean Multnomah in- and out-migration rates by year and type of household:

$$M_{hit} = \alpha + \sum_{k} \beta_k \, \mathbf{1}[\text{Year}_t = k] \times X_{kh} + \mathbf{Z}_h' \boldsymbol{\gamma} + \varepsilon_{hit}, \tag{4}$$

where X_{kh} is the specific characteristic (e.g., whether they have young children) and $\mathbf{Z}_h$ is a vector of other controls. In this way we can see how the estimated probability of moving changes during the time period for people with that characteristic, holding all others constant. The β_k's are the estimated conditional means by year.

We then separately estimate the decision to move out of and then into Multnomah County in a DiD framework, using likely unaffected households as the control group. To estimate out-migration, we estimate the following equation for all observations living in Multnomah in time $t-1$ (the year before the ACS survey):

$$M_{ht} = \alpha + \beta \, (\text{Post}_t \times \text{HighEd}_h) + \delta_t + \mathbf{X}_h' \boldsymbol{\theta} + \varepsilon_{ht}, \tag{5}$$

where $M_{ht} = 1$ if the individual (h) lived in a different county from Multnomah in time t and equals zero if they stayed in Multnomah. Here we use an individual's educational attainment as a proxy for income: we assume that those with a college education or more are more likely to be exposed to the higher tax rates, which due to the progressive nature of Multnomah's tax begin to bite over \$125K in income. This allows us to avoid two problems that come from estimating treatment status using observed income: endogeneity and timing. The first concern is standard in this literature: a change in tax policy could induce a change in income, meaning that using income as a treatment indicator creates a simultaneity issue. The second concern is unique to the ACS: in this dataset, we observe the income in year $t+1$ (the destination year), not year t (the year prior to the decision to move). Therefore, we observe the income after the realization of the migration decision, which is likely to be influenced by that decision. The estimated coefficient β is predicted to be positive as it captures the "push" effects of PFA; i.e., how much more likely is the treated person to leave after the policy is enacted. We also estimate the full event-study version.

In-migration is estimated with a similar model. However, modeling in-migration is trickier because there are 388 counties (in the ACS) in which those moving to Multnomah could be living in time $t-1$. This yields a much larger sample for which the number of in-migrants from any given county in any year is going to be zero for the vast majority of those counties. We therefore estimate the same model as the one above for out-migration, but with two samples of individuals: all those in the lower 48 states plus DC, and all those in California, Washington, and Oregon. Both samples exclude, for obvious reasons, those individuals in Multnomah County. Therefore, $M_{ht} = 1$ if the individual (h) moved to Multnomah in year t. The only other change to the equation above is the inclusion of origin-county fixed effects. Now, the coefficient of interest β is predicted to be negative as it captures the reduced "pull" of Multnomah on the treated person due to the PFA.[11]

[11] For out-migration, the sample consists of Multnomah County residents only, so we use heteroskedasticity-robust standard errors. For in-migration, the sample draws from many origin counties with potentially correlated unobservables, so we cluster standard errors at the origin county level.

While we attempt to isolate causal effects using this multi-pronged approach and multiple comparisons, we acknowledge that other factors occurred at the same time as PFA and so may be confounding our results. The Covid-19 pandemic and the numerous social and economic changes it wrought is a primary culprit. To try to address this concern, in both sets of targeted exercises we use placebo counties as an additional check, on top of an extensive number of robustness checks.

5 Estimated Effects on Migration Behavior

Following the organizational structure in Figure 3, we first compare the migration behaviors observed from the two different data sources before investigating each one in more detail. Table 2 reports the in-, out-, and net in-migration rates for the 8 affected counties, before and after the PFA, across the different data sources and measures. The top panel compares the in- and out-migration rates, before and after PFA, for the AGI measure. It further reports the ACS measures for the period that matches the IRS (2021–2022) and the longer period (2021–2024). The bottom panel reports the change in the net in-migration rate, which best reflects the impact on the county population, for the two different data sources and measures (AGI and households/number of returns).

Several findings emerge from this table. The head-to-head comparisons between the IRS and ACS data for the same time period are reasonably close, especially for Multnomah. More generally, they not surprisingly are more similar in the higher population counties; recall the ACS is unavailable for the least populated ones (Yamhill, Columbia, and Skamania). In the two years immediately following the PFA for which all measures are available, out-migration from Multnomah grew substantially while in-migration declined only slightly (panel A), leading to an approximate 3% (1.4 to 2%) decline in net in-migration in AGI (returns; panel B). The neighboring Oregon county of Washington saw similar patterns and a decline in its net in-migration rate of about half that size. Most of the other key counties were much less affected. Clark County, in Washington, appears to be the primary beneficiary, lending some credence to concerns that residents are not only leaving Multnomah, but the state of Oregon as well. Appendix Tables A1 and A2 provide additional context by comparing Multnomah County's and Oregon's migration rates, respectively, to the national distribution of counties and states.

5.1 Synthetic Difference-in-Differences Results

We estimate an enormous number of SDID models using: (1) two data sources (IRS and ACS); (2) alternative subsets (for IRS, all counties vs. only those also in ACS; for ACS, ending in 2022 vs. going through to 2024); (3) three different units of migration (AGI, returns/households, exemptions/individuals); (4) different pools of donor counties; and (5) with and without covariates (for counties in the ACS, the covariate set includes property taxes). For these five combinations, we further estimate SDID models and event studies for in-migration, out-migration, and net in-migration. We distill this enormous number of estimates into something interpretable by using the summary device of specification curves for the main difference-in-differences results and by focusing on a few baseline models for the event studies. The full set of results are available upon request.

Figure 4 reports the specification curves for AGI—the unit most relevant for revenue consequences—for the three migration rates (in-, out-, and net in-migration). The corresponding specification curves for returns/households and exemptions/individuals are reported in Appendix Figures A1 and A2 and tell a consistent story, though the effects are typically less statistically significant. These curves provide three salient findings. First, the effect on net in-migration is always negative and usually statistically significant, with effects ranging from approximately -1 to -4 percentage points. This is a sizable impact that brackets the simple changes reported in Table 2. As expected, including covariates tends to reduce the magnitude, as does using the smaller set of urban donor counties, but neither affects the basic conclusion. In contrast, using the ACS versus the IRS has little systematic impact, which is reassuring. Second, this decline in net in-migration is driven primarily by increased out-migration from Multnomah. Out-migration is consistently positive, almost always statistically significant (even more so than net in-migration), and ranges from approximately 0.6 to 3 percentage points for AGI. In-migration tends to be negatively affected, especially for AGI, but is rarely statistically significant. Third, across all three units, AGI is consistently more strongly affected, both in magnitude and statistical significance, than returns/households or exemptions/individuals. This finding is intuitive because AGI best captures that it is higher income households who are more likely affected by PFA's tax. Taken together, these findings are strongly consistent with the simple descriptives in Table 2 and reinforce the conclusion that the two different data sources yield reasonably similar conclusions.

In choosing benchmark models to emphasize in the paper, we focus on AGI because it most accurately reflects differences by income and is the most relevant outcome for revenue consequences. As shown in the appendix specification curves (Figures A1 and A2), the results for the other two units are similar but typically less statistically significant. We also focus on specifications with covariates, to limit omitted-variable bias, and that exclude 2020, to reduce confounding from Covid-19. Within that set, we highlight four SDID benchmark specifications: IRS vs. ACS college, each estimated using the all-counties donor pool and the stringency-matched donor pool. These four benchmarks align with the main comparative strengths of the two data sources while spanning a broad and a tighter donor-pool definition.

To keep Figure 6 readable, it reports the all-counties pair from that highlighted set: IRS all-counties and ACS college all-counties, both with covariates and 2020 excluded. The stringency-matched counterparts are highlighted in the specification curves and treated as companion benchmark estimates throughout the paper. Note that this exercise is not of much help in detecting pre-trends because satisfying the pre-trends requirement is the criterion for choosing the synthetic control in SDID. Rather, these figures are helpful in seeing if SDID succeeded in this way and also to see if the effect is growing or diminishing as time passes.

Overall, these event studies confirm our conclusions from the SDID; out-migration is the primary, statistically significant driver of the sometimes statistically significant decline in net in-migration. The event studies that use the longer period covered by the ACS college sample suggest that the effect on out-migration at first grows and then diminishes in the last year of the sample (2023–2024). The shorter IRS sample (through 2022) suggests a stable effect during that short time period.

To investigate how much PFA may be inducing households to move across state lines and thus affect state revenues, we repeat the above analyses using a definition of migration that is limited to moving out-of-state. That is, we estimate the models using only the subset of moves that also results in a changed state of residence. We use only the IRS data for this exercise because it contains the full set of counties and thus all out-of-state moves. Figure 5 reports the same specification curves as Figure 4 but restricted to interstate moves (and to the IRS-derived migration measures), and yields similar results. Out-migration to a different state is around two percentage points higher in Multnomah, relative to other counties, after the PFA. In-migration (from out of state) is slightly lower but rarely statistically significant. The combined effect on net in-migration (to/from another state) is thus negative, around 2.5 percentage points and typically statistically significant.

In sum, the SDID results and event studies tell a consistent story of AGI/incomes leaving Multnomah County in the years after the PFA was passed, with a possible decline in the very last year. The estimated magnitudes are meaningful as they suggest an approximate 2.5 percentage point increase in out-migration, which is a substantial increase over the rates observed in 2018–2019 (5.8 and 7%; see Table 2). There is also suggestive evidence that it discouraged AGI/incomes from moving into Multnomah, but the magnitude is much smaller and rarely statistically significant. All of these effects extend to moving out of Oregon as well.

5.2 Analyses of IRS Migration Flows

Continuing the strategy laid out in Figure 3, we first use the IRS county-to-county flows to explore where taxpayers/AGI are moving to and from. Figure 7 shows the change in where taxpayers originally in Multnomah County, measured by AGI, moved to after the policy change (2021+). That is, it shows how the outflows from Multnomah changed after PFA; which counties received more (red) or fewer (blue) AGI than before PFA. Because nearly all of the nontrivial changes occurred in the Pacific Northwest, Figure 7 focuses on those states/counties. The results for the entire U.S., as well as this same exercise using returns or exemptions instead of AGI, are reported in the Appendix (Figure A3).

These figures make clear that nearly all of the substantial change in outflows from Multnomah were increases to neighboring counties in Oregon and Washington. Somewhat surprisingly, the biggest recipients were neighboring Oregon counties, especially Washington County, followed by Columbia and Hood River. Only Clark County, across the border in Washington, was impacted to a similar extent. These patterns reinforce the findings of Wilson (forthcoming) about the barriers to crossing state lines and suggest that concerns about the state losing tax revenues may be overblown.

Figure 8 reports a similar exercise for those moving into Multnomah County. Again, because nearly all of the changes occurred in these three states, we focus on them and report other variations in the Appendix (Figure A4). Figure 8 shows many more blue areas, which represent a decrease in inflows to Multnomah from each county. The biggest decline, by far, occurred in Clackamas County, but all counties bordering Multnomah saw declines in AGI leaving them for Multnomah. The only counties that sent relatively more residents (AGI) to Multnomah were within Oregon and a good distance away from Multnomah.

We formalize this analysis by estimating several variations of the PPML flow model written above in Equation (3). This approach considers the flow patterns of all U.S. counties and also allows us to control for other time-varying county characteristics that could affect migration. Recall that the ACS only reports county information for a small subset of counties

(389), which means we can only include the full set of controls (which include property taxes) for this smaller subset. We therefore estimate these models on the full set of counties and the smaller ACS subset, including all of the available controls.

In addition to the standard DiD model written in Equation (3), where Multnomah is a "treated" origin (OutPost) and a "treated" destination (InPost), we also estimate event-study variations. By allowing these push and pull effects to differ in every period, we can test for pre-trends and explore the dynamic effects of the policy.

The results from these event studies, shown for AGI including all possible controls for both samples, are reported in Figure 9, which plots the origin (out-migration) and destination (in-migration) coefficients together. For both samples, the results are quite similar, especially for the estimated impacts of PFA (the "after" period). In the years after PFA, both effects are statistically significant, of a similar magnitude, and strongly suggestive that the PFA increased out-migration and decreased in-migration. The PPML coefficients of 0.1 to 0.2 are semi-elasticities (approximate proportional changes in the flow count), which are not directly comparable to the SDID estimates expressed in percentage points of the migration rate. The smaller magnitudes reflect the different estimand: PPML identifies the effect on the level of bilateral flows between county pairs, while SDID identifies the effect on the county-level migration rate normalized by the AGI stock.[12] Moreover, the estimated effects are not statistically significantly different if all covariates are excluded. These figures therefore provide strong evidence that the PFA did in fact lead to a population loss in Multnomah County, both from more taxpayers leaving and fewer moving in.

The results for the period before the PFA are less than ideal, especially for in-migration, which seems to have been slightly decreasing since 2016. Out-migration, too, is sometimes statistically significant although it does not exhibit as strong a pattern over time. Nonetheless, both the out-migration (push) and in-migration (pull) effects are markedly different and

[12] In the PPML framework, the coefficient β represents the proportional change in the expected bilateral flow: $E[y_{ij}] = \exp(\mathbf{X}'\beta)$. A coefficient of 0.15 thus corresponds to approximately a 15% increase in the bilateral flow count, conditional on origin-destination fixed effects.

in the expected direction after the PFA is passed.

To further explore the veracity of our results, we conduct a placebo exercise where we systematically re-estimate the model allowing each of the other counties to be the "treated" origin and destination. If Multnomah and the PFA are being uniquely affected, then few of these placebo push and pull effects should be statistically significant, except for Type I error. An overarching concern of our analysis is that the PFA coincided with the Covid-19 pandemic; this exercise helps address that concern directly.

Figure 10 shows the results of this exercise for the full set of IRS counties; the ACS subset is similar and available upon request. Panels (a)–(b) show the distribution of the placebo estimates of $\hat{\beta}_1$ (out-migration), denoting Multnomah's estimated place in the distribution. Only 3.4% of the estimated coefficients are larger, reasonably close to what would be expected due to Type I error (2.5%). The t-statistics reveal a similar pattern with only 4.4% being larger than Multnomah's. Panels (c)–(d) perform the same exercise for $\hat{\beta}_2$ (in-migration) and, similar to the event-study and SDID analyses above, yield similar but weaker results. Here, 15.6% (8%) of the estimated coefficients (t-statistics) are smaller—more negative— than Multnomah's. Taken together, our analyses of the IRS flow data strongly suggest that migration patterns into—and especially out of—Multnomah were affected by the passage of the PFA.

5.3 Analyses of ACS, Individual-Level Data

Our last set of analyses asks the question of *who* is doing the moving and is yet another test of the veracity of our basic findings. Are the people who are actually moving the ones we would expect to be affected by the policy? To abstract away from endogenous decisions to go to college, get married, etc., we limit this part of our analyses to those over age 24.

Returning again to Figure 3, we first provide some descriptive statistics revealing what kinds of people are moving into and out of Multnomah County in the years before and after the policy is enacted. To better isolate the pattern for each individual characteristic, we estimate a simple model of in- or out-migration as in Equation (4). In this way we can see how the estimated probability of moving changes during the time period for people with that characteristic, holding all others constant. The β_k's are the estimated conditional means by year.

We estimate and plot these conditional means for age, education, income, number and ages of children, marital status, and gender. The full set is reported in the Appendix (Figure A5), but for parsimony we focus on income, education, and age of the youngest child, reported in Figure 11. We focus on these characteristics here because this analysis is primarily descriptive. In the DiD models below, we avoid using income and age of youngest child due to their endogeneity, even more so as they are measured in year 2—the year after the move took place. Instead, the DiD models use being college-educated as a proxy for being "treated" by the tax associated with PFA.

The first two sets of plots show that the highest income group (\$200K+) and the college-educated group had the biggest increases in their conditional mean probability of moving out of Multnomah after PFA. The probability of moving into Multnomah seems less consistently affected, although these two groups again had the clearest, though modest, declines. These results show that it is the "treated" group that appears to have changed the most and that a college education appears to be a reasonable proxy for higher-income households.

Advocates of PFA argue that the universal preschool may attract young families to Multnomah, and so Figures 11e and 11f report the patterns by the age of the youngest child. These plots reveal no substantial difference among the groups; all groups are moving out of (into) Multnomah at increasing (decreasing) rates after PFA. However, this measure also suffers from being observed in year 2 and may be endogenous, and it also misses those families who are planning to have a child. The patterns by age group, reported in Figures A5a and A5b, yield similar results that all age groups are behaving reasonably similarly.

An overarching tendency of these plots across all characteristics is that the biggest increases in out-migration, at least, are in the years immediately after 2020. The out-migration rates appear to be declining and perhaps returning to close to their pre-PFA levels by the last year of the ACS, 2024. This suggests that perhaps the impact on migration—and thus tax revenues—may be dissipating.

Our last set of exercises, the bottom box on the right-hand side of Figure 3, is to estimate DiD and event-study models of out-migration and in-migration, written in Equation (5) above, using college-educated and then age group as the "treated" group. Figure 12 reports the event studies for the decision by individuals of certain groups to move out of Multnomah County, using college-educated and then age group as a proxy for being "treated." The corresponding regression coefficients are reported in Table A3. Figure 12a supports the evidence provided so far, that college-educated households are disproportionately leaving Multnomah County after PFA; there is also little evidence that the assumption of parallel pre-trends is violated. It furthermore suggests the effects are statistically significant and similar in magnitude—2 to 3 percentage points higher—for every year after the PFA. These results suggest that the effects of the PFA on the out-migration of higher-educated households, proxied by college education, persist.

To address Governor Kotek's and others' concern that PFA is driving high income households out of Oregon state, we re-estimate the model using whether the individual moved out of state, reported in Figure 12b. While understandably less precise (as the sample of movers is considerably smaller), the results strongly suggest the concern is warranted. The differential out-of-state migration patterns are negligible before PFA and jump to nearly 2 percentage points afterwards.

Figures 12c and 12d report the same two exercises using the youngest (25–44) and oldest (65+) as differentially treated from the middle age group. The youngest are the most likely to be attracted by the universal preschool policy, and the oldest are the most likely to not have their incomes come from Multnomah County (and thus still be subject to the tax even if they moved out). The estimates suggest little difference between the age groups and the patterns that do appear are contrary to our expectations; younger households are moving out at higher rates and older households may even be seeing a decline relative to other groups. Layering this exercise upon the college-educated one—i.e., allowing the "treatment" effect to differ by age, a triple-difference—exaggerates these patterns (see Figure A6). The college-educated young are more strongly affected than the oldest college-educated households, relative to non-college-educated groups.

Lastly, we analyze the impact of PFA on the decision to move into Multnomah County. As noted above, there are two ways this exercise differs from the out-migration DiD models. First, we use two different samples, one that includes individuals living in all 388 counties observed in the ACS (leaving out Multnomah) and another that limits the sample to those living in counties in California, Oregon, and Washington, which are the predominant "sending" areas. Because the results are fairly similar, we report the ones from the full sample. The second difference is that we include origin county fixed effects. These results are reported in Figure 13 by college education (Figures 13a and 13b) and by age (Figures 13c and 13d). Mirroring the results we have seen throughout the paper, in-migration seems much less impacted than out-migration, with statistically insignificant declines of small magnitudes using college-educated and few differences across age groups. However, considering both age and college education together (a DDD), reported in Figure A6, suggest that Multnomah did indeed become a less desirable location for older college-educated households, relative to their younger peers.

Having established that PFA appears to have meaningfully altered migration patterns—increasing out-migration and, to a lesser extent, dampening in-migration—we now turn to quantifying the fiscal consequences of these behavioral responses. The next section develops a microsimulation model to translate the estimated migration effects into revenue impacts for both Multnomah County and the state of Oregon.

6 Estimated Effects on Tax Revenues

Across all of the different data sources and empirical methodologies, the results suggest a similar story: higher-income households, as measured directly by AGI in the IRS flows and proxied in the ACS by college education alongside descriptive income patterns, appear to be moving out of Multnomah at substantially higher rates after PFA. Some of these households also appear likely to be moving out of Oregon altogether, lending support to state policymaker concerns. The in-migration of those groups may likewise have been dampened, although the effect is less robust. In contrast, we find no evidence that PFA is attracting younger households, as their behavior is following similar patterns as the general population. These results therefore suggest that the PFA likely had a negative impact on the tax base in Multnomah County and the state of Oregon and thus may have led to decreased tax revenues. This section attempts to quantify those possible effects.

We want to estimate the revenue effects of the PFA, inclusive and exclusive of migration effects. This includes both the effect on Multnomah County and the state of Oregon. Importantly, given data limitations, this paper focuses solely on state and local income tax revenue. Because Oregon does not have a state sales tax, this restriction should have minimal effects on the overall state revenue effects. However, local revenue sources, like property taxes, are excluded, which means the migration adjustment is a lower-bound on the revenue effects on the county.

6.1 Microsimulation Tax Model

We begin by taking the ACS sample of Multnomah County residents in 2019, and construct tax units using data on income and household characteristics.[13] We then re-weight the

[13] The ACS has many, but not all, of the income characteristics necessary to construct tax units. We start with personal income (wage, self-employment, investment, welfare, and total), and aggregate up to the couple level if we can observe both partners. We subtract welfare income out of total income to get the sum of taxable income (with a floor of $0). Any remaining amount of taxable income not captured by the enumerated income categories (wages, self employment, and investment) is captured in other property income. We randomly simulated itemized deductions by AGI cell to match the 2019 IRS totals.

sample to match the 2019 county-level IRS statistics by AGI brackets, targeting the number of returns, number of married filing jointly returns, total AGI, and total wages by AGI bracket. This calibration uses a generalized regression (GREG) estimator to ensure the re-weighted ACS sample accurately reflects the county's tax filing population. The income characteristics of this re-weighted sample are then inflated to 2022 USD, providing a sample of tax units that abstracts from potential migration effects.

This sample is then run through NBER's TAXSIM program (Version 35) to obtain state tax rates and, importantly, state taxable income. With state taxable income, we can run a simple local income tax calculator to estimate the revenue raised from the PFA tax.

6.2 Baseline Revenue Estimates

According to our estimates, in 2022 the PFA was simulated to raise $189 million, had the basic composition of tax units not changed over the course of 2019–2022. Notably, this closely matches actual 2022 PFA revenue of $187 million, suggesting the simulated tax base accurately reflects the county's filing population.

6.3 Revenue Effects of Migration

To account for migration effects, we draw on the four highlighted SDID benchmark specifications discussed earlier: IRS vs. ACS college crossed with all-counties vs. stringency-matched donor pools, each estimated with covariates and excluding 2020. For the main revenue calculations, we use the IRS $\times$ all-counties benchmark because it relies on the broadest donor pool and maps most directly into the countywide AGI revenue exercise.[14] Using this benchmark, we estimate that there is a 3.7 percentage point increase in out-migration of AGI from Multnomah County overall, equal to $1.4 billion in AGI leaving Multnomah County.

[14]The microsimulation applies the AGI-weighted average effective tax rate to the lost AGI, implicitly assuming that out-migrants have the same income distribution as all impacted filers. To the extent that higher-income households are disproportionately likely to leave—as our DiD results suggest—the effective marginal rate on departing AGI exceeds the average rate, and the revenue loss estimates here are conservative.

When limited to out-of-state migration, this falls to a 2.3 percentage point increase, equal to $0.9 billion. The $1.4 billion in AGI would have brought in approximately $16 million in PFA revenue, or about 8.5 percent of the conventional revenue estimate. We can take our static estimate of the revenue effect of the PFA – $189 million – and subtract the migration revenue loss calculated above – $16 million – to get our post-migration annual revenue of the PFA tax – $173 million. This remains very close to the actual revenue raised by the tax ($187 million), but does suggest that our initial simulated base was too small, potentially reflecting captured bracket creep or economic growth.

For the state, we likewise use the IRS × all-counties interstate benchmark and calculate the lost state income tax revenue of $78.6 million in 2022, or about 2.7 percent of state income tax revenue from Multnomah County. The remaining three highlighted specifications are shown as comparison points in the revenue-distribution figures.

6.4 Distribution of Revenue Estimates

To convey the uncertainty around these revenue estimates, we use the full distribution of SDID point estimates from the specification curve analysis. For each specification, we apply the implied migration-adjusted AGI loss to the microsimulation model, yielding a distribution of revenue effects. Figure 14 plots the resulting histograms for the PFA and Oregon state income tax, respectively. The PFA revenue loss estimates are centered around $16 million (8.5% of baseline), with the interquartile range spanning roughly $10–$22 million. The Oregon state revenue loss distribution is wider, reflecting the additional uncertainty in the out-of-state migration estimates, but is centered around $79 million.

6.5 What Drives Variation in the Estimates?

With over 2,800 specifications in the SDID analysis, it is helpful to understand which modeling choices drive the most variation in the estimated effects. Figure 15 reports the results of a meta-regression that decomposes the variance in the specification curve estimates of the AGI net in-migration effect. The two panels show the estimated influence of each specification dimension for inter-county and interstate migration, respectively. Across both, the choice of donor pool—and in particular the restriction to Covid-matched counties—has the largest influence on the estimated effect, followed by whether 2020 is excluded and the choice of data source (IRS vs. ACS). The inclusion of covariates has a relatively modest influence, which is reassuring given that covariate selection is often a source of researcher degrees of freedom. Appendix Figure A7 reports the analogous decomposition separately for out-migration and in-migration.

7 Concluding Remarks

The goal of this research is to provide the best possible evidence of the causal effects of Multnomah County's Preschool for All (PFA) policy and its associated progressive income tax on cross-county and cross-state migration and, subsequently, on tax revenues. We use two different sources of publicly available data, each with its own relative strengths and weaknesses, combined with a range of causal inference methods to provide estimates of the policy's effects on migration into and out of Multnomah County. We then use those estimates to calculate the likely effect on tax revenues. Because Multnomah County borders Washington state, which has no income tax, we also investigate the impact on migration into and out of Oregon state and the consequences for state income tax revenues.

The findings of all these analyses are consistent: AGI-based IRS measures and college-proxy ACS measures both indicate elevated out-migration from Multnomah County and the state of Oregon in the years after PFA was passed. They are doing so at higher rates relative to other similar metropolitan areas and relative to lower income groups. These results are robust to a wide range of empirical approaches, sensitivity and robustness checks, and placebo tests. Migration into Multnomah County, especially for those same groups, also appears to have slowed after PFA was passed, although the effects are less salient than for out-migration. These estimates suggest that the diminished tax base due to changes in migration reduced the income tax generated through the policy by about 8.5%, a modest but nontrivial amount. That some of this migration extended across the Oregon border also led to a reduction in state income tax revenues, coming from Multnomah County, of $78.6 million in 2022 or about 2.7% of the revenues generated there. Given that Multnomah County is considered the main economic engine in Oregon, this relatively small decline could still have an outsized effect on state coffers.

While we have tried to control for confounding factors in multiple ways, we acknowledge that PFA was enacted during the Covid-19 pandemic and that other factors, such as the George Floyd protests and Measure 110, also occurred around this time. We cannot rule out that the migration effects we observe are caused at least in part by these other events. However, the fact that we see the strongest effects among households most likely to be exposed to the tax—measured directly through AGI in the IRS data and proxied by college education in the ACS—lends support to the view that PFA is at least partially responsible. We also find no evidence that the promise of universal, tuition-free preschool led to an influx of households likely to benefit. This result could be due to the delayed and incomplete roll-out of the program.

For all of these reasons, we view the estimated migration and revenue effects as likely an upper bound on what would occur in other settings. The timing of the PFA coincided with events—the pandemic, protests, and changes in drug enforcement—that independently increased the mobility of higher-income residents. While Oregon's taxation of non-resident income earned in the state may discourage some tax-induced moves, this factor is likely dwarfed by the confluence of other push factors during this period. The unique location of Multnomah County on the Washington border and the delayed, incomplete rollout of the preschool program also seem likely to have exaggerated the estimated impact. And, while it appears clear that net in-migration to Multnomah County has declined during this period, driven mostly by out-migration, the magnitude of the effects is not large. The modest magnitude is not surprising given the relatively low rates at which people move across county and, especially, state lines. Nonetheless, this research cautions against dismissing the concern that taxes on high income households may lead substantial numbers to leave, at least when such taxes are imposed at a small geographic scale such as a city or county.

It also casts an interesting light on proposed new taxes on very high income/high wealth taxpayers in Oregon's two neighboring states, California and Washington.[15] On the one hand, our results suggest that such taxes may very well lead affected households to leave; on the other, the fact that we observe most households move to a bordering county suggests that coordination among these states could help mitigate the effects. More generally, it underscores once again the challenges of enacting programs funded with progressive taxation, at the local level.

[15] See https://www.nytimes.com/2026/01/23/opinion/california-wealth-tax-billionaires.html and https://www.washingtonpolicy.org/publications/detail/gov-fergusons-income-tax-proposal-would-make-seattle-1-for-highest-taxes.

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Tables

Table 1: County Characteristics and Tax Rates in the Portland MSA

County	Population	Median HH Income	Per Capita Income	Marginal Tax Rate $150K	Marginal Tax Rate $300K
Multnomah County (State + Metro + PFA)					
Multnomah	815,428	69,176	63,806	12.4%	13.9%
Metro counties (State + Metro)					
Washington	600,372	82,215	67,358	10.9%	10.9%
Clackamas	421,401	80,484	64,685	10.9%	10.9%
Other Oregon counties (State only)					
Marion	345,920	59,625	49,042	9.9%	9.9%
Yamhill	107,722	63,902	51,040	9.9%	9.9%
Columbia	52,589	62,257	49,655	9.9%	9.9%
Washington State counties (no income tax)					
Clark	503,311	75,253	57,344	—	—
Skamania	12,036	65,181	54,468	—	—

Notes: Population from 2020 Decennial Census. Median household income from ACS 2015–2019 5-year estimates. Per capita income from BEA CAINC1 (2020). Marginal tax rates shown for a single filer at the indicated income level (2021+). Oregon state income tax: 9.9% on income above $125K. Metro Supportive Housing Services tax: 1% on income above $125K (Multnomah, Washington, Clackamas counties). Preschool for All (PFA) tax: 1.5% on income above $125K, rising to 3% above $200K (Multnomah County only). Married filing jointly thresholds are $200K (Metro, PFA bracket 1) and $400K (PFA bracket 2). Washington State has no personal income tax.

Table 2: Migration Rates for Multnomah County and Neighboring Counties

Panel A: In- and Out-Migration Rates (AGI)

	In-Migration Rate (%)					Out-Migration Rate (%)				
	IRS		ACS			IRS		ACS		
County	18–19	21–22	18–19	21–22	21–24	18–19	21–22	18–19	21–22	21–24
Multnomah	6.59	6.27	6.00	6.00	5.29	7.01	9.68	5.42	8.70	7.82
Neighboring OR counties										
Washington	6.02	6.06	5.00	5.62	5.22	6.10	7.51	5.14	6.87	5.40
Clackamas	6.49	8.10	5.81	7.34	6.46	5.82	6.72	4.45	5.91	5.11
Marion	5.17	5.37	4.55	4.55	4.20	5.30	5.44	4.27	4.32	4.69
Yamhill	6.62	7.27	–	–	–	5.27	6.81	–	–	–
Columbia	6.33	6.67	–	–	–	5.26	5.94	–	–	–
Neighboring WA counties										
Clark	5.98	7.76	5.17	8.22	7.27	4.72	5.85	4.48	5.01	4.37
Skamania	8.52	9.11	–	–	–	5.65	6.01	–	–	–
All other OR counties	6.76	7.63	5.56	5.16	5.09	5.09	6.01	4.27	5.65	4.73
All other WA counties	5.32	5.68	5.16	4.91	4.62	4.89	6.01	4.43	5.28	4.77

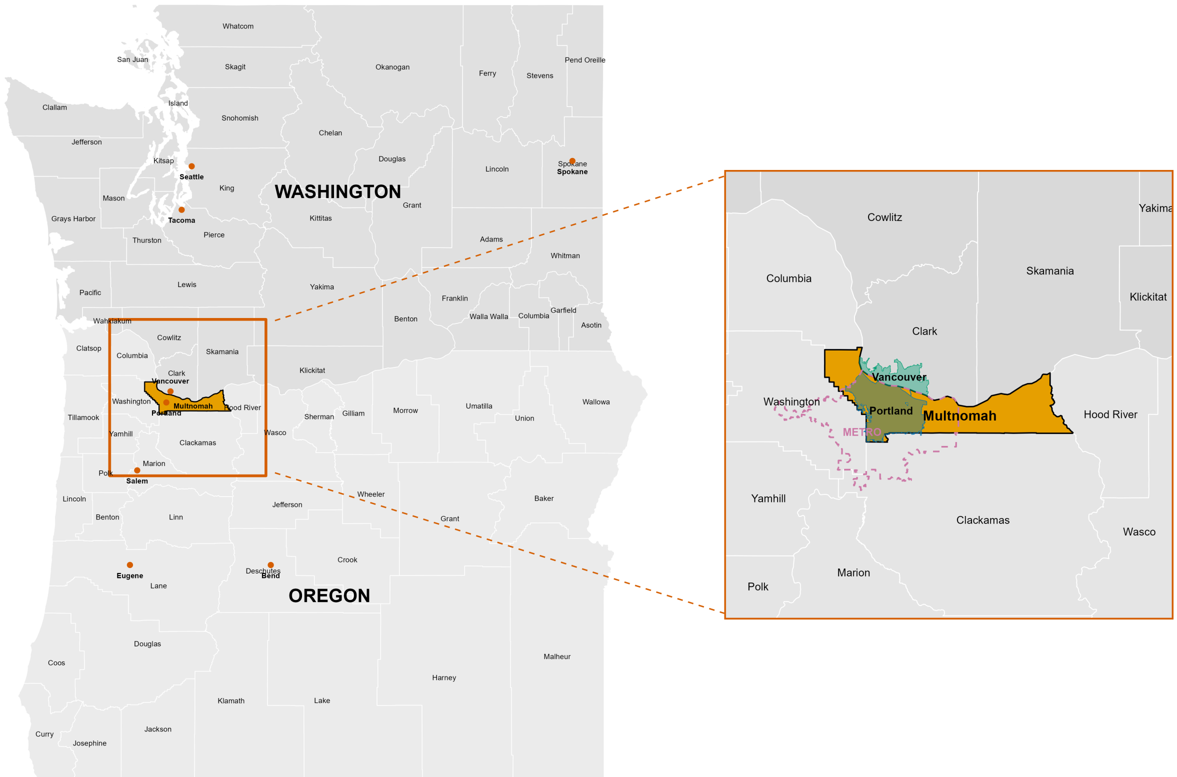
Panel B: Change in Net In-Migration Rate (percentage points)

	AGI / Dollars			Returns / Households		
County	IRS	ACS (21–22)	ACS (21–24)	IRS	ACS (21–22)	ACS (21–24)
Multnomah	-2.98	-3.28	-3.11	-1.44	-1.95	-1.41
Neighboring OR counties						
Washington	-1.37	-1.11	-0.04	-0.71	-0.69	-0.36
Clackamas	0.72	0.07	-0.01	-0.50	0.63	0.45
Marion	0.05	-0.04	-0.76	-0.55	0.21	0.01
Yamhill	-0.89	–	–	-0.24	–	–
Columbia	-0.33	–	–	-0.41	–	–
Neighboring WA counties						
Clark	0.65	2.52	2.21	-0.18	1.22	0.97
Skamania	0.23	–	–	0.51	–	–
All other OR counties	-0.05	-1.79	-0.93	-0.53	-1.39	-0.66
All other WA counties	-0.77	-1.10	-0.88	-0.64	-0.78	-0.51

Notes: Panel A reports in- and out-migration rates measured in AGI (IRS) or dollars (ACS) as a percentage of the base filing/survey population for each county-period. Panel B reports the change in the net in-migration rate (in-rate minus out-rate) between periods, in percentage points, for AGI/dollars and returns/households. Pre-period averages tax years 2018–2019; IRS post-period covers 2021–2022; ACS post-periods cover 2021–2022 and 2021–2024. indicates county not identified in the ACS. Source: IRS Statistics of Income; American Community Survey.

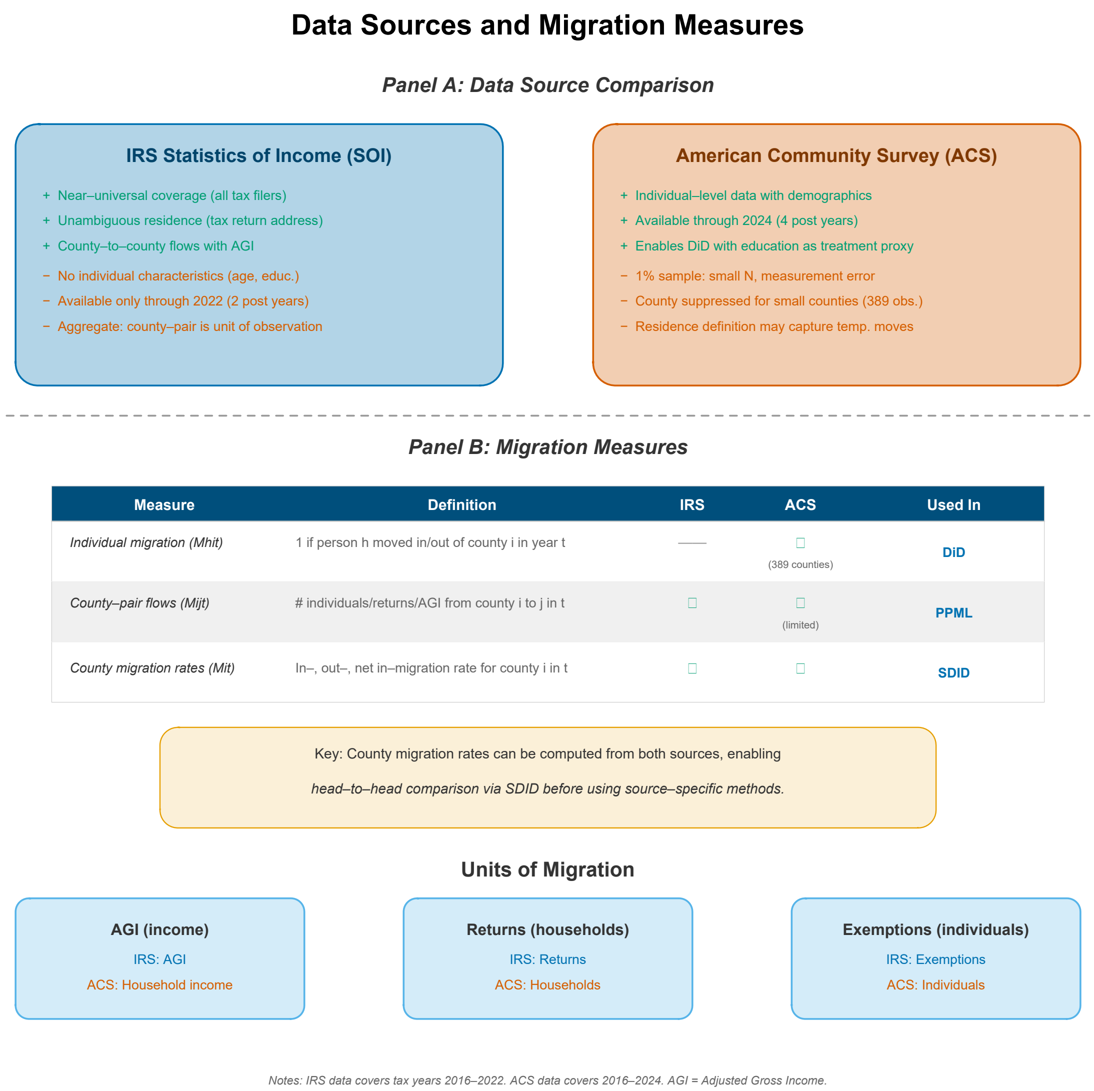
Figures

Figure 1: Map of Multnomah County and the Portland Metropolitan Area



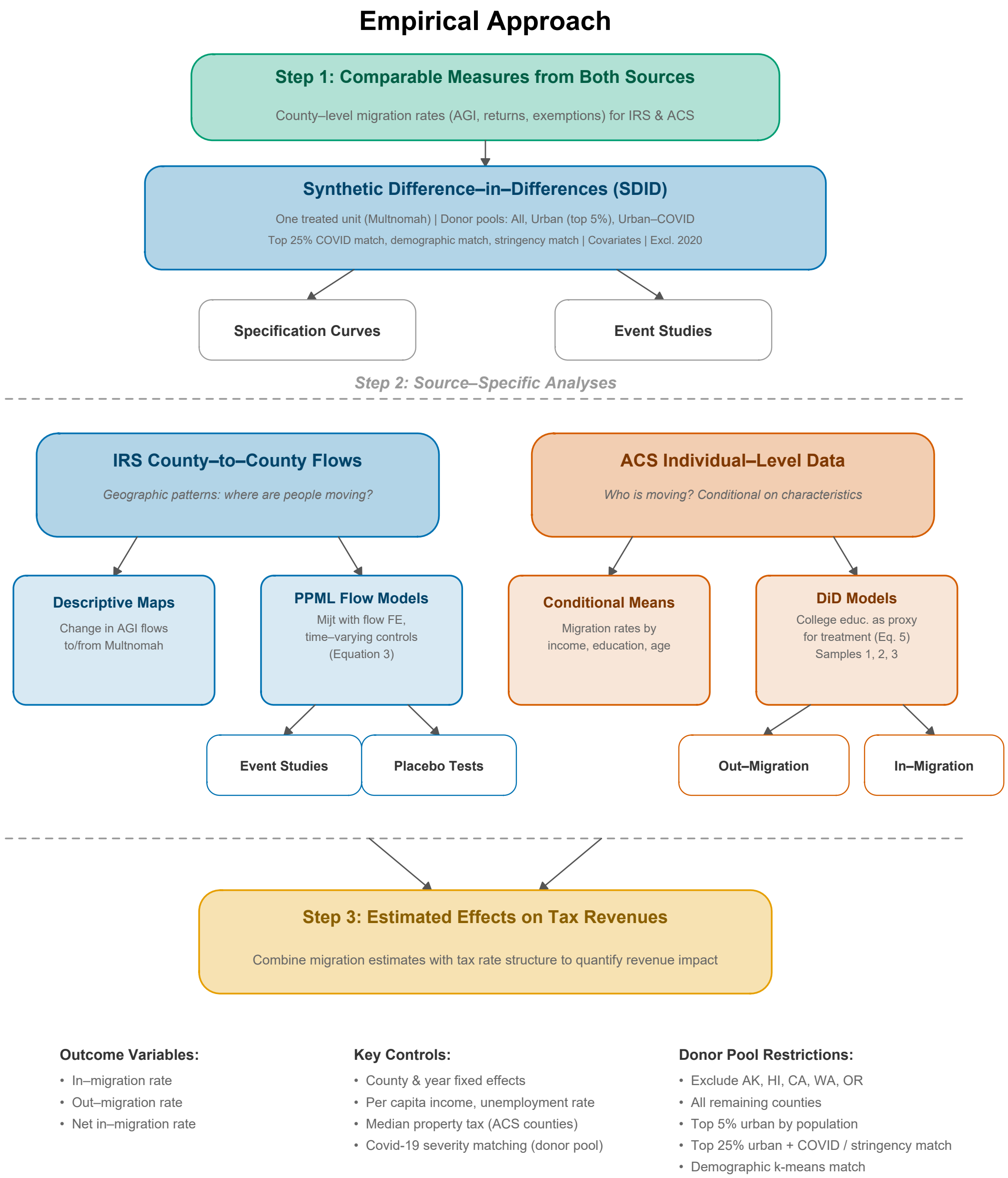
Notes: Map shows Multnomah County (shaded) within the Portland-Vancouver-Hillsboro MSA. Inset shows the Metro regional government boundary (purple dashed outline), which covers 24 cities in Clackamas, Multnomah, and Washington counties. Source: U.S. Census Bureau TIGER/Line shapefiles.

Figure 2: Data Sources and Migration Measures



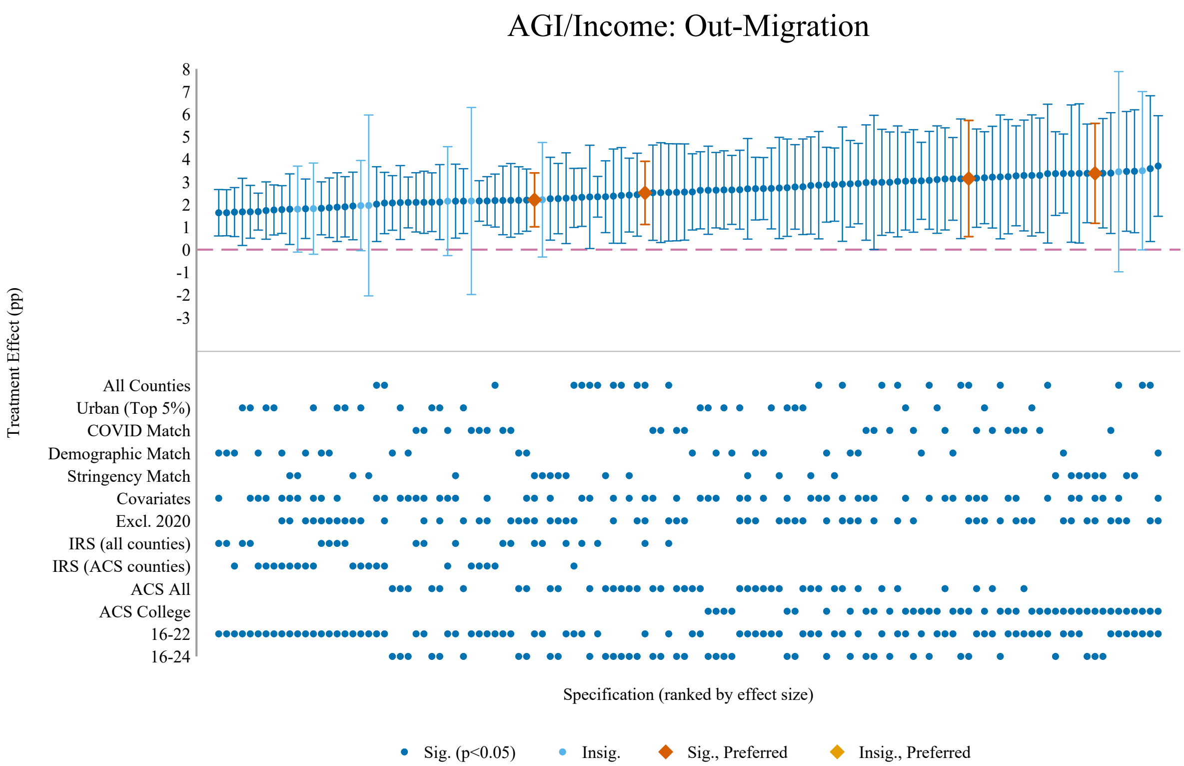
Notes: Top panel summarizes the advantages and disadvantages of the IRS SOI county-to-county flow data and the ACS microdata. Bottom panel describes the migration measures constructed from each source and the empirical methods applied to each. See Section 3 for details.

Figure 3: Empirical Approach



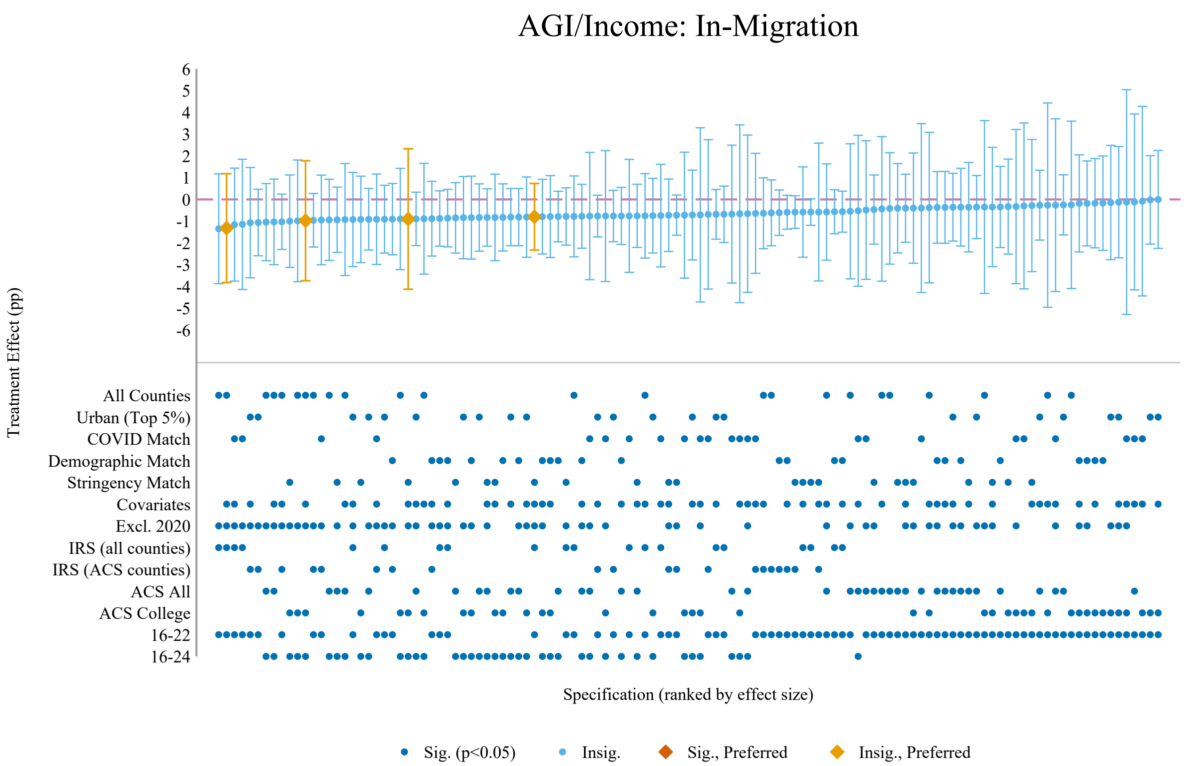
Notes: Schematic overview of the empirical strategy. The center column shows the SDID approach applied to both data sources for direct comparison. The left branch details the IRS-specific analyses (geographic flow patterns, PPML models, placebo tests). The right branch details the ACS-specific analyses (conditional means by household characteristics, individual-level DiD models). See Section 4 for details.

Figure 4: SDID Specification Curves: AGI Migration Rates
(a) Out-Migration



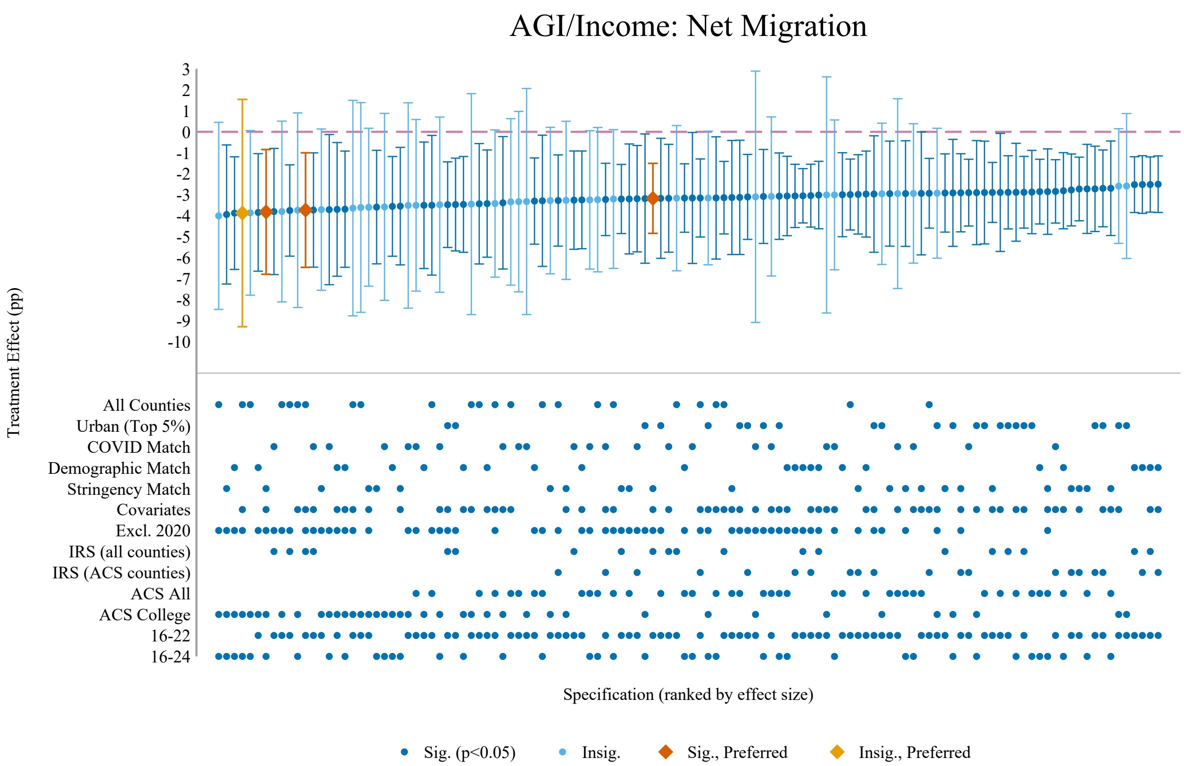
Notes: Each point represents a separate SDID estimate of the effect of PFA on the AGI out-migration rate from Multnomah County. Specifications vary by data source (IRS vs. ACS), donor pool (all counties, urban top-5%, urban-Covid matched, demographic match, stringency-matched), and inclusion of covariates. Highlighted points correspond to the four benchmark specifications discussed in the text: IRS vs. ACS college, each shown with all-counties and stringency-matched donor pools. Whiskers show 95% confidence intervals based on placebo inference. Year 2020 is excluded from all specifications. Source: Authors' calculations using IRS SOI county-to-county flow data (2016–2022) and ACS microdata (2016–2024).

Figure 4: SDID Specification Curves: AGI Migration Rates
(b) In-Migration



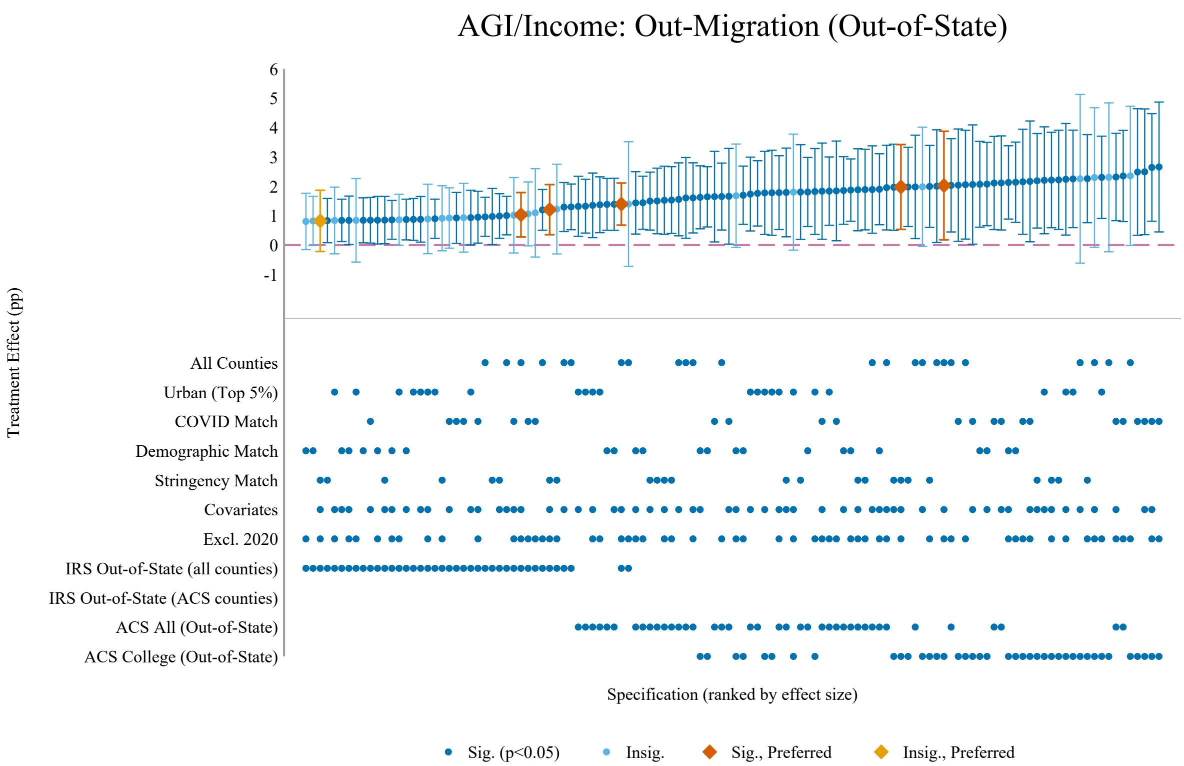
Notes: See notes to panel (a). Outcome is the AGI in-migration rate to Multnomah County.

Figure 4: SDID Specification Curves: AGI Migration Rates
(c) Net In-Migration



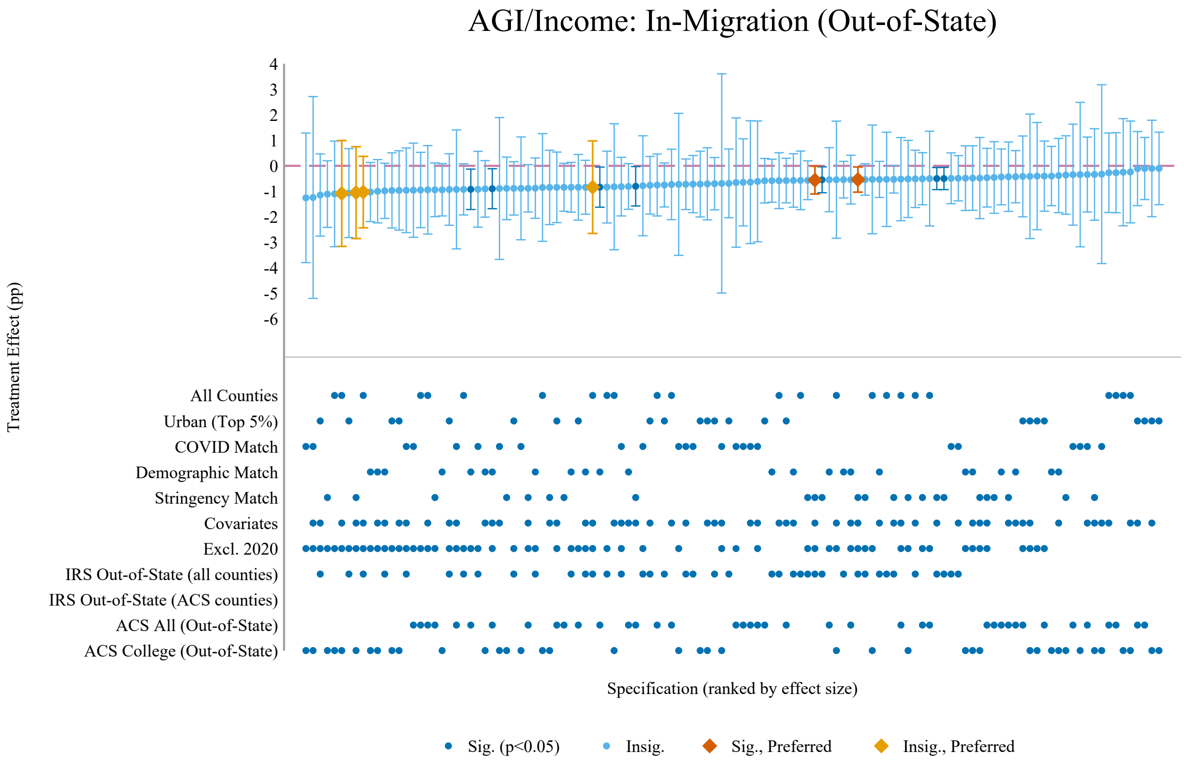
Notes: See notes to panel (a). Outcome is the AGI net in-migration rate for Multnomah County (in-migration minus out-migration).

Figure 5: SDID Specification Curves: AGI Interstate Migration Rates
(a) Out-Migration



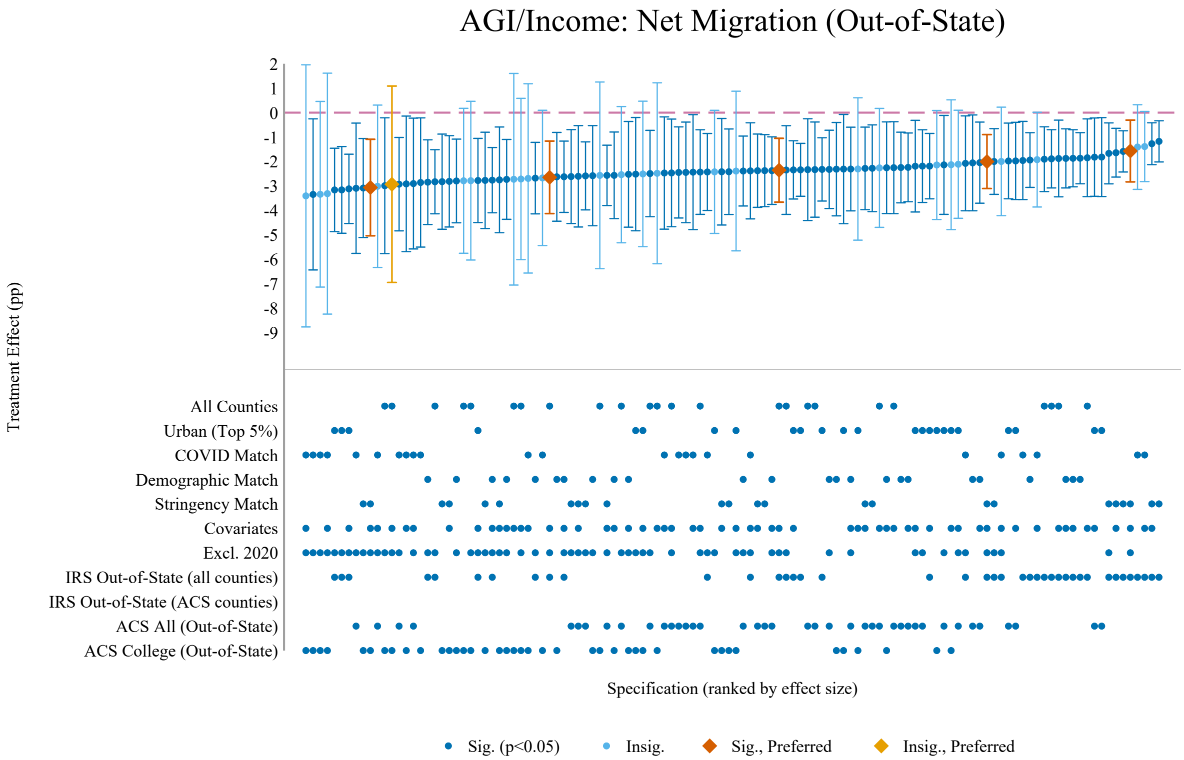
Notes: Each point represents a separate SDID estimate of the effect of PFA on the AGI out-of-state migration rate from Multnomah County. Only interstate moves (IRS type 5) are included. Specifications vary by donor pool (all counties, urban top-5%, urban-Covid matched, demographic match, stringency-matched) and inclusion of covariates. Highlighted points correspond to the IRS all-counties and IRS stringency-matched benchmark specifications discussed in the text. Whiskers show 95% confidence intervals based on placebo inference. Year 2020 is excluded from all specifications. Source: Authors' calculations using IRS SOI county-to-county flow data (2016–2022).

Figure 5: SDID Specification Curves: AGI Interstate Migration Rates
(b) In-Migration



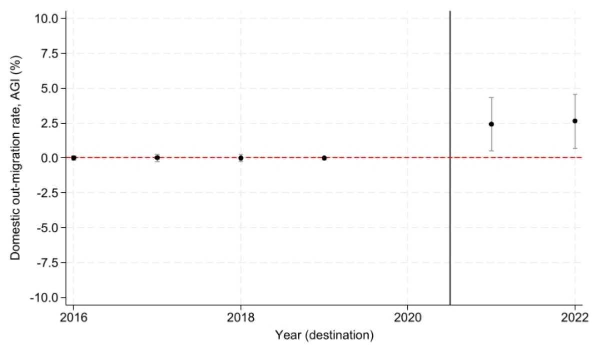
Notes: See notes to panel (a). Outcome is the AGI in-migration rate to Multnomah County from other states.

Figure 5: SDID Specification Curves: AGI Interstate Migration Rates
(c) Net In-Migration

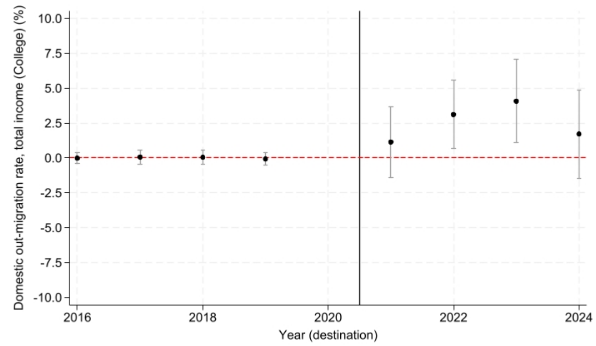


Notes: See notes to panel (a). Outcome is the AGI net interstate in-migration rate for Multnomah County (in-migration from other states minus out-migration to other states).

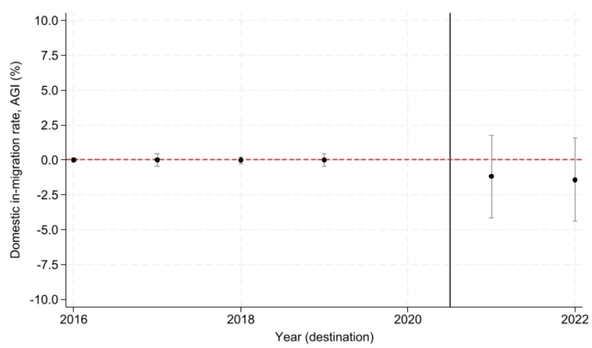
Figure 6: SDID Event Studies: All-Counties Benchmarks



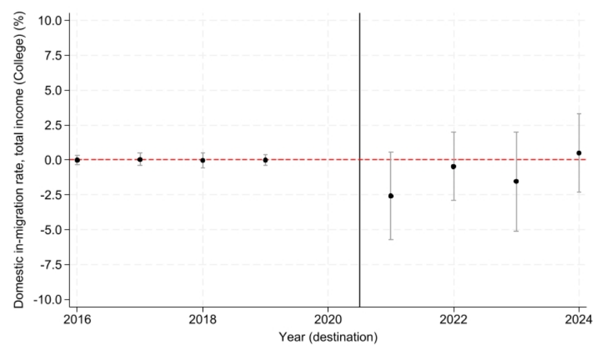
(a) Out-migration, IRS



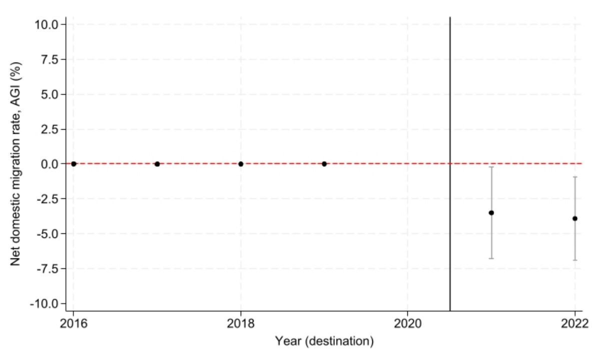
(b) Out-migration, ACS



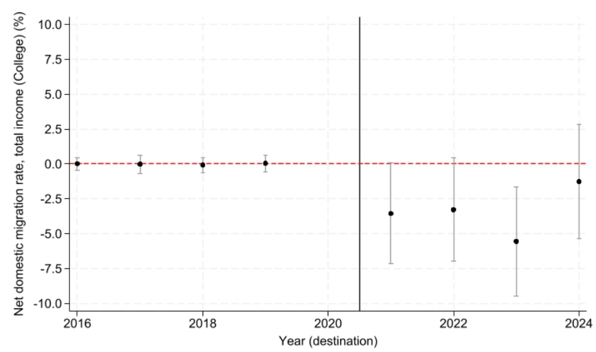
(c) In-migration, IRS



(d) In-migration, ACS



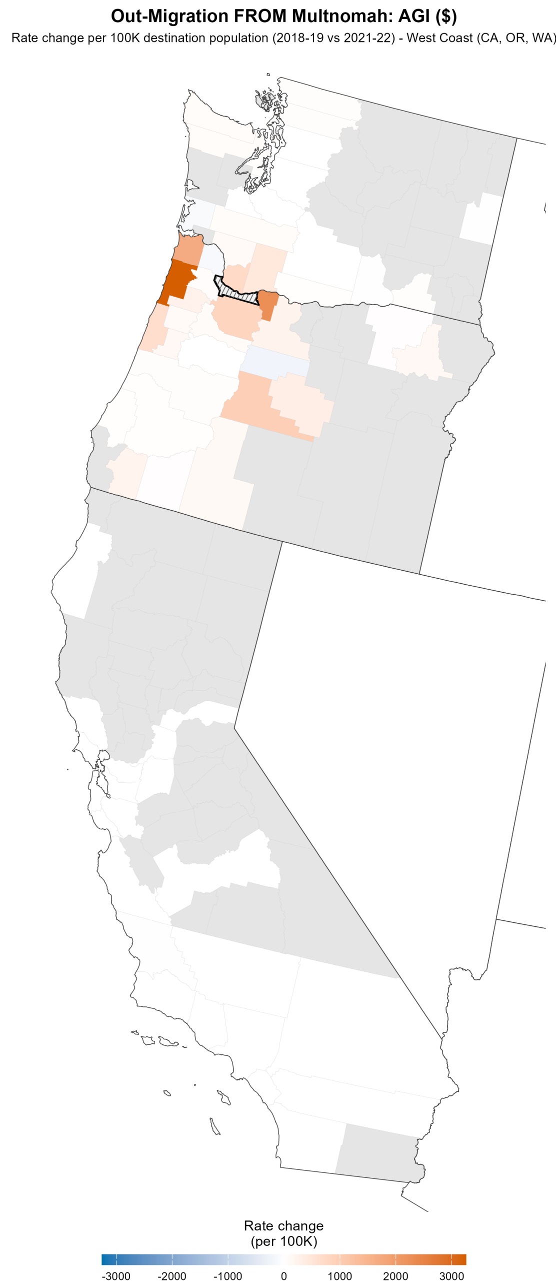
(e) Net in-migration, IRS



(f) Net in-migration, ACS

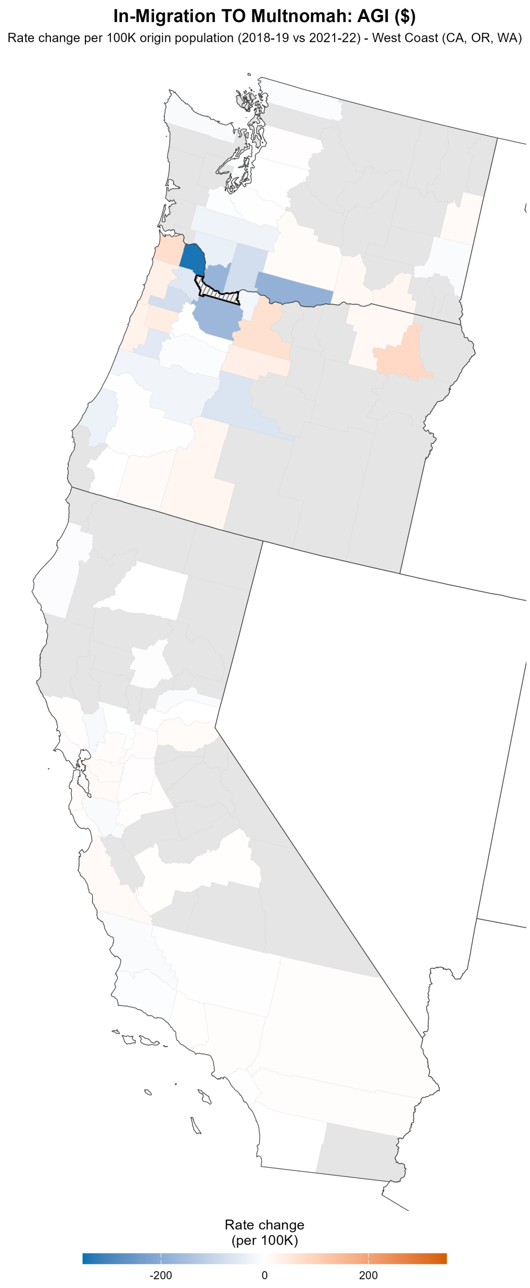
Notes: SDID event study estimates of the effect of PFA on AGI migration rates, with 2019 as the base year and 2020 excluded. Left column uses IRS SOI data (2016–2022) with the full set of donor counties; right column uses the ACS college sample (2016–2024) with the full set of donor counties. These panels therefore show the all-counties pair from the four highlighted benchmark specifications discussed in the text. All specifications include time-varying county-level covariates. Shaded areas show 95% confidence intervals based on placebo inference. Source: Authors' calculations using IRS SOI county-to-county flow data and ACS microdata.

Figure 7: Change in AGI Outflows from Multnomah County After PFA (Pacific Northwest)



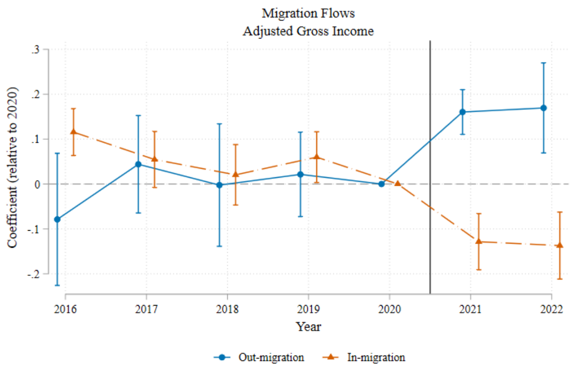
Notes: Map shows the change in AGI outflows from Multnomah County to each destination county, comparing the pre-PFA period (2018–2019 average) to the post-PFA period (2021–2022 average). Changes are expressed as rate changes per 100,000 destination county population. Red shading indicates increased outflows; blue indicates decreased outflows. Multnomah County shown hatched; gray counties had zero flows in one or both periods. Source: Authors' calculations using IRS SOI county-to-county flow data.

Figure 8: Change in AGI Inflows to Multnomah County After PFA (Pacific Northwest)

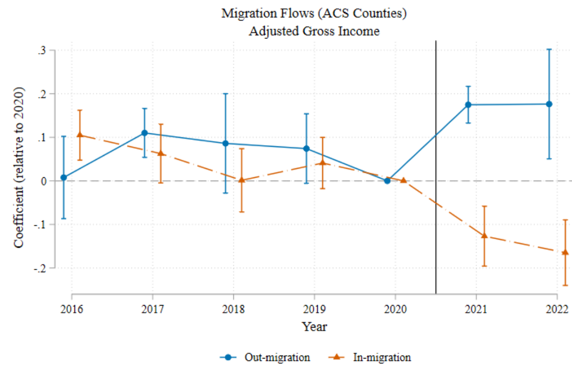


Notes: Map shows the change in AGI inflows to Multnomah County from each origin county, comparing the pre-PFA period (2018–2019 average) to the post-PFA period (2021–2022 average). Changes are expressed as rate changes per 100,000 origin county population. Red shading indicates increased inflows; blue indicates decreased inflows. Multnomah County shown hatched; gray counties had zero flows in one or both periods. Source: Authors' calculations using IRS SOI county-to-county flow data.

Figure 9: PPML Flow Model Event Studies: AGI, with Controls



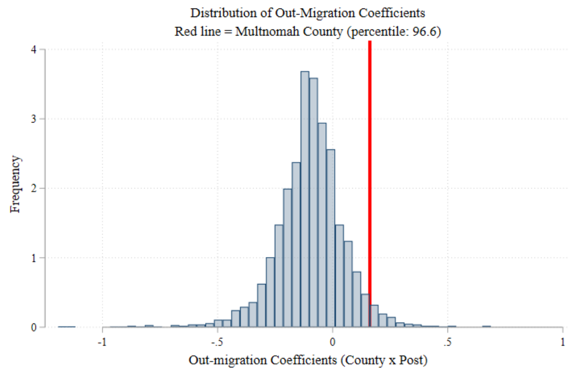
(a) IRS Counties



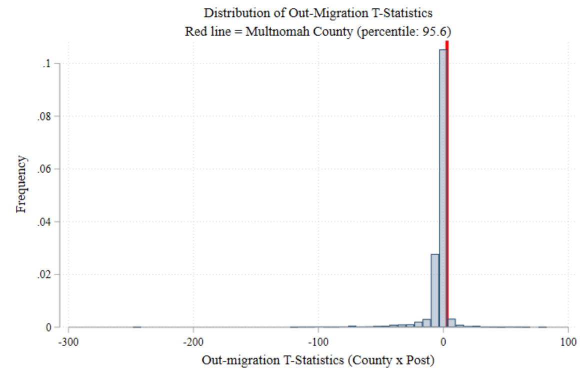
(b) ACS Counties

Notes: Poisson pseudo-maximum likelihood (PPML) event study estimates showing both the push effect (out-migration from Multnomah, origin coefficient) and pull effect (in-migration to Multnomah, destination coefficient) on AGI flows on the same plot, with 2019 as the base year. All specifications include county-pair fixed effects, year fixed effects, and time-varying county-level controls (per capita income, unemployment rate, property taxes where available). Panel (a) uses the full IRS county sample. Panel (b) uses the ACS county subset. Whiskers show 95% confidence intervals. Source: Authors' calculations using IRS SOI county-to-county flow data.

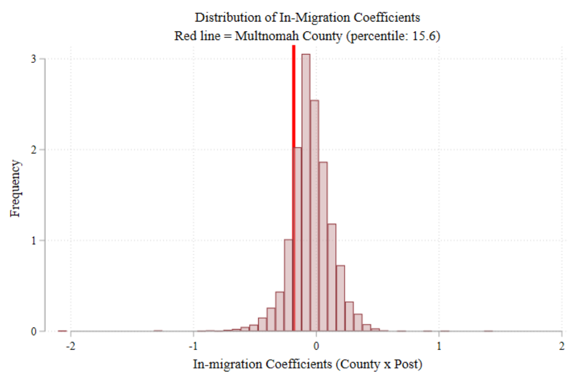
Figure 10: Placebo Distributions of PPML Estimates



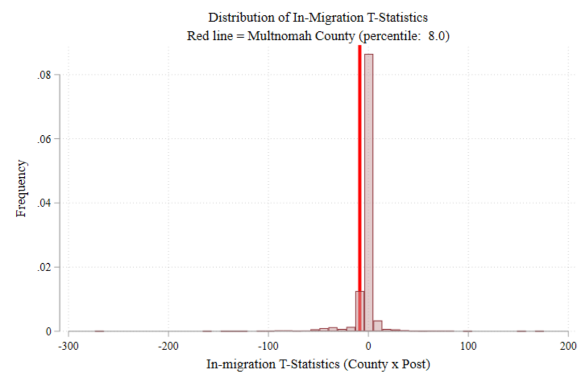
(a) Out-migration: coefficients



(b) Out-migration: t-statistics



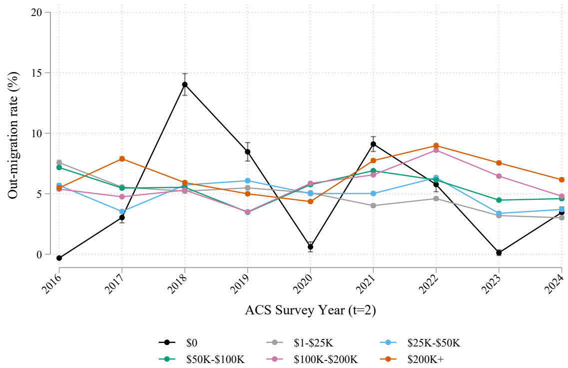
(c) In-migration: coefficients



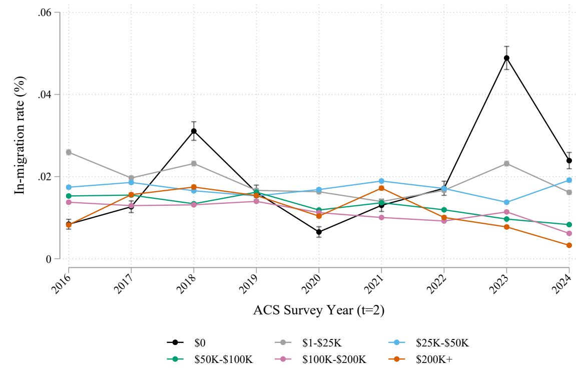
(d) In-migration: t-statistics

Notes: Distribution of placebo PPML estimates obtained by systematically re-estimating the model with each non-Multnomah county assigned as the "treated" origin (panels a–b) or destination (panels c–d). Multnomah's estimated effect is marked with a vertical dashed line. Panels (a) and (c) show coefficient distributions; panels (b) and (d) show t-statistic distributions. Only 3.4% of out-migration placebo coefficients exceed Multnomah's; 15.6% of in-migration placebo coefficients are more negative. Source: Authors' calculations using IRS SOI county-to-county flow data (full county sample).

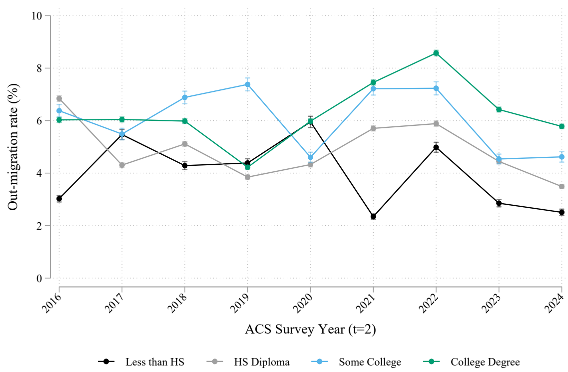
Figure 11: Conditional Mean Migration Rates by Household Characteristics



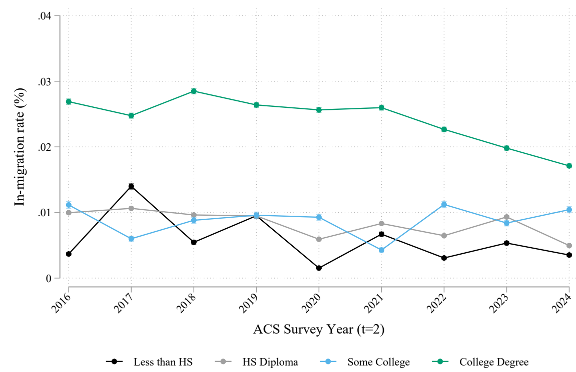
(a) Out-migration by income



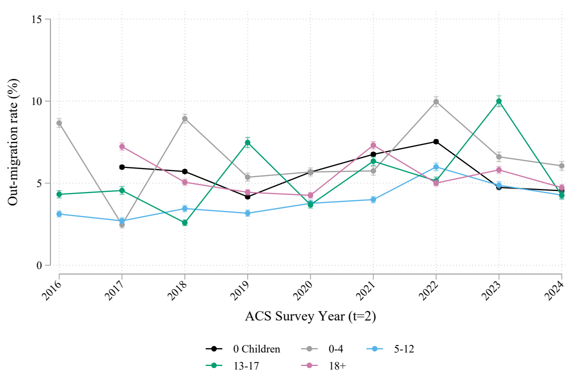
(b) In-migration by income



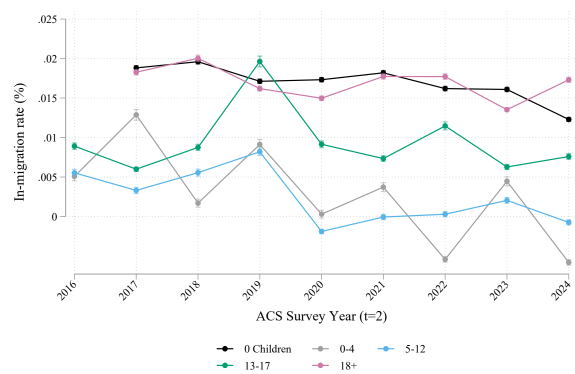
(c) Out-migration by education



(d) In-migration by education



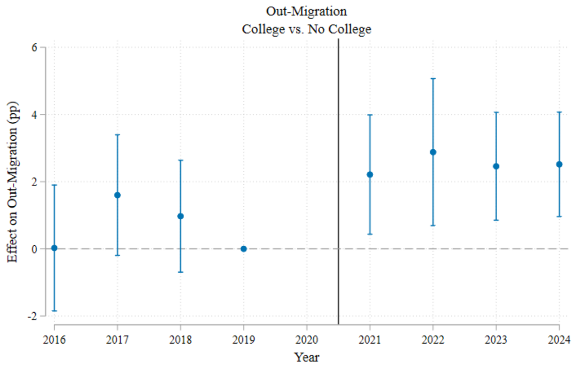
(e) Out-migration by age of youngest child



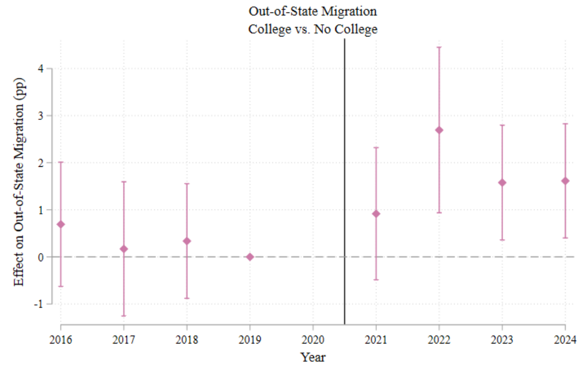
(f) In-migration by age of youngest child

Notes: Conditional mean in- and out-migration rates for Multnomah County by year and household characteristic, estimated from Equation (4). Left column: out-migration. Right column: in-migration. Rows: total family income categories (top), educational attainment (middle), and age of youngest child (bottom). All other household characteristics are controlled for. Source: Authors' calculations using ACS microdata (2016–2024). Sample restricted to ages 25+.

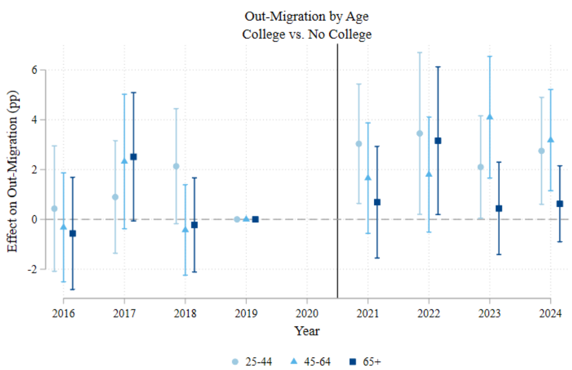
Figure 12: DiD Event Studies: Out-Migration from Multnomah County



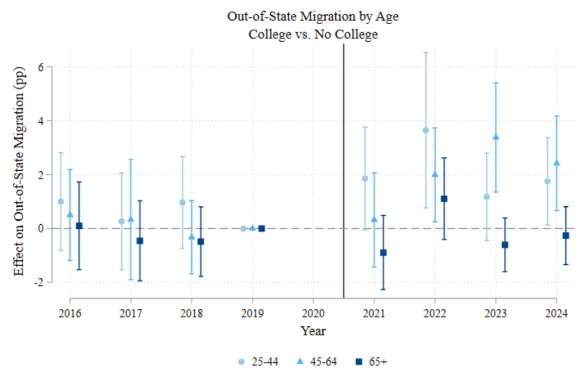
(a) College, any county move



(b) College, out-of-state move



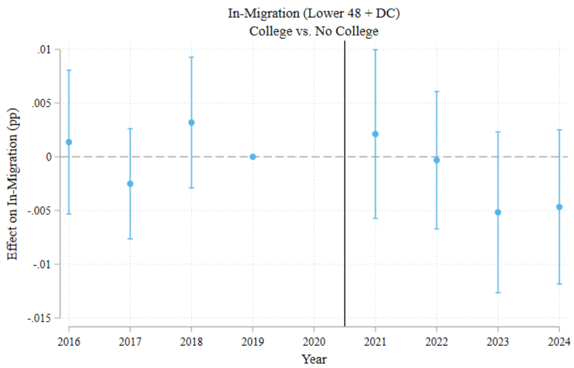
(c) Age group, any county move



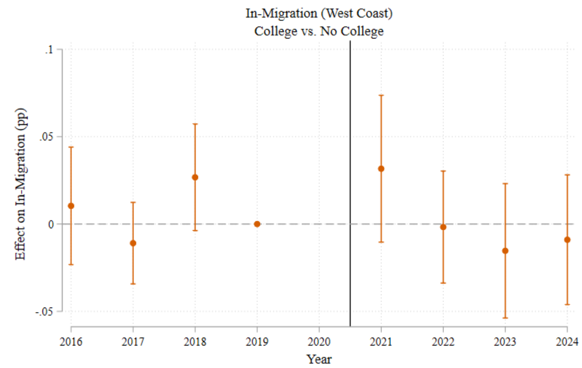
(d) Age group, out-of-state move

Notes: Event study estimates of out-migration from Multnomah County, with 2019 as the base year and 2020 excluded. Top row: college-educated vs. non-college as treatment proxy (left: any county move; right: out-of-state move). Bottom row: age group as treatment, with 45–64 as the omitted reference group (left: any county move; right: out-of-state move). All specifications absorb year and categorical controls (age, sex, marital status, children, education). Robust standard errors. Whiskers show 95% confidence intervals. Source: Authors' calculations using ACS microdata (2016–2024). Sample: Multnomah County residents aged 25+.

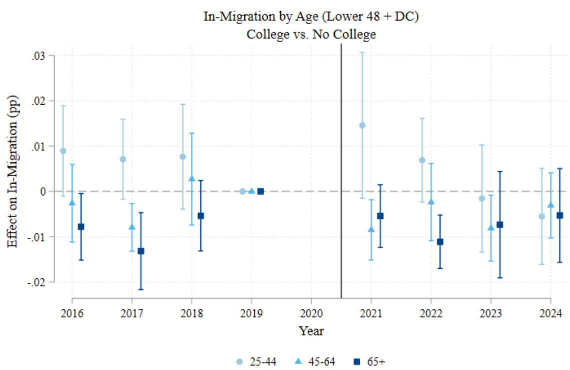
Figure 13: DiD Event Studies: In-Migration to Multnomah County



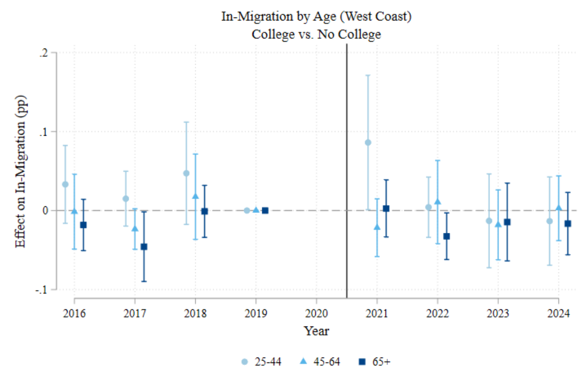
(a) College, lower 48 + DC



(b) College, CA/OR/WA



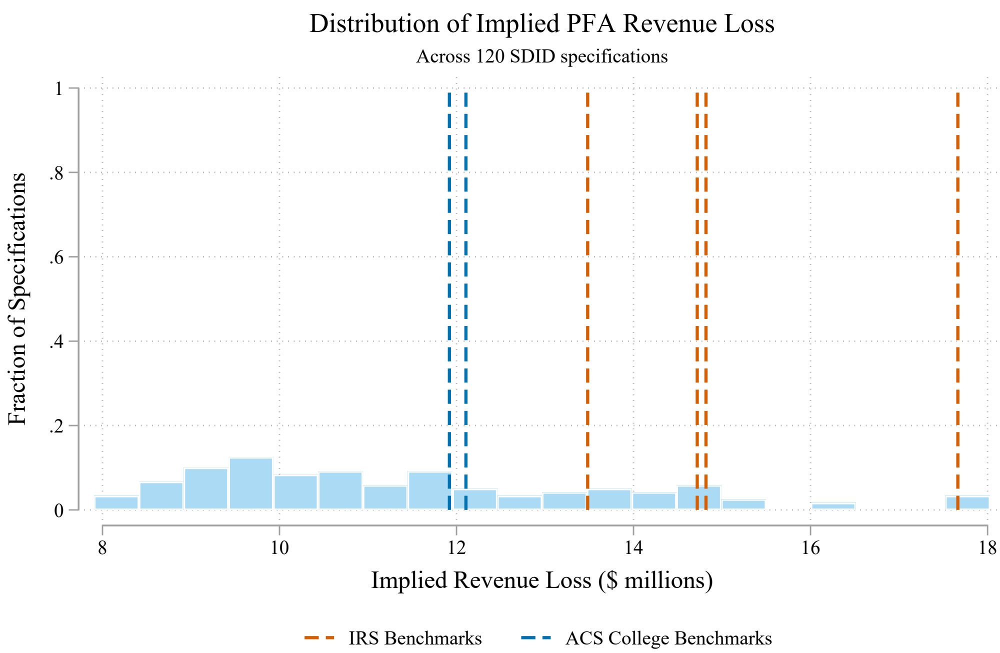
(c) Age group, lower 48 + DC



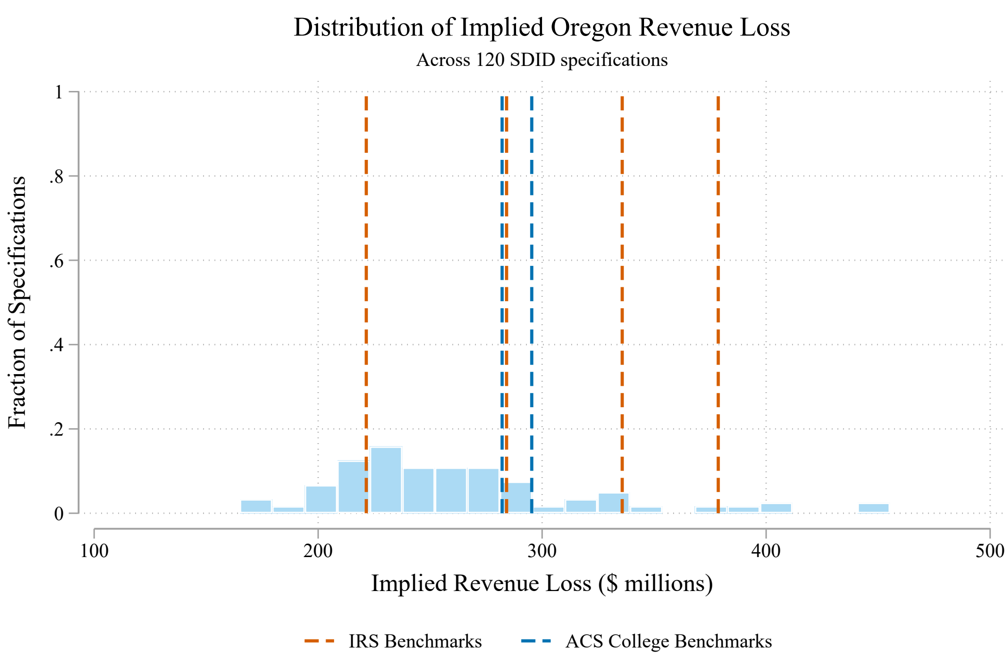
(d) Age group, CA/OR/WA

Notes: Event study estimates of in-migration to Multnomah County, with 2019 as the base year and 2020 excluded. Top row: college-educated vs. non-college as treatment proxy (left: lower 48 + DC sample; right: CA/OR/WA sample). Bottom row: age group as treatment, with 45–64 as the omitted reference group (left: lower 48 + DC; right: CA/OR/WA). All specifications include origin county fixed effects, year fixed effects, and categorical controls. Standard errors clustered by origin county. Whiskers show 95% confidence intervals. Source: Authors' calculations using ACS microdata (2016–2024). Sample: ages 25+, excluding Multnomah County residents.

Figure 14: Distribution of Estimated Revenue Effects Across Specifications



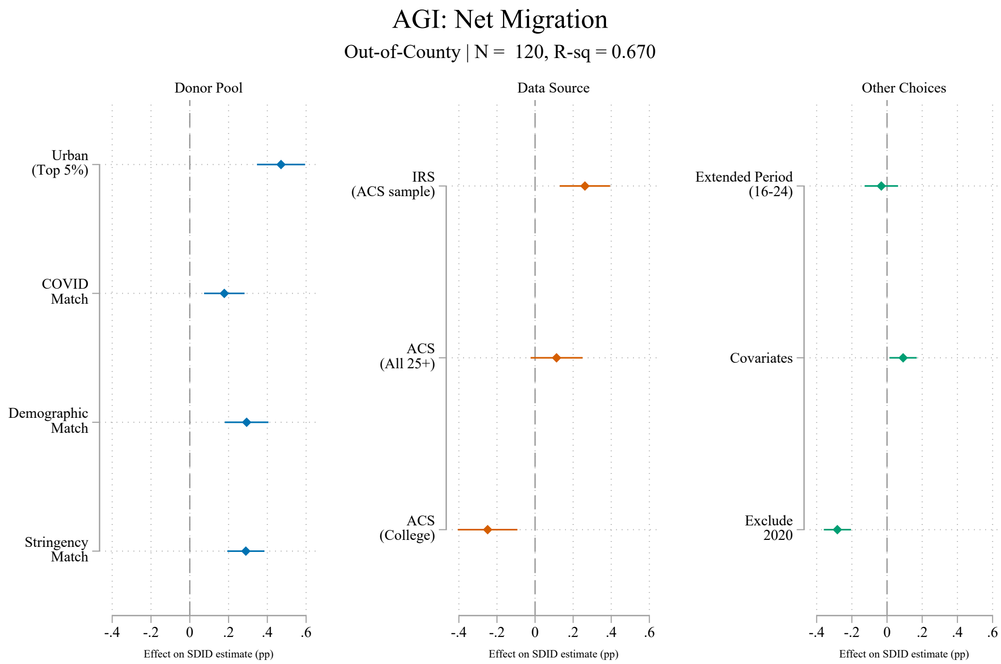
(a) PFA revenue loss



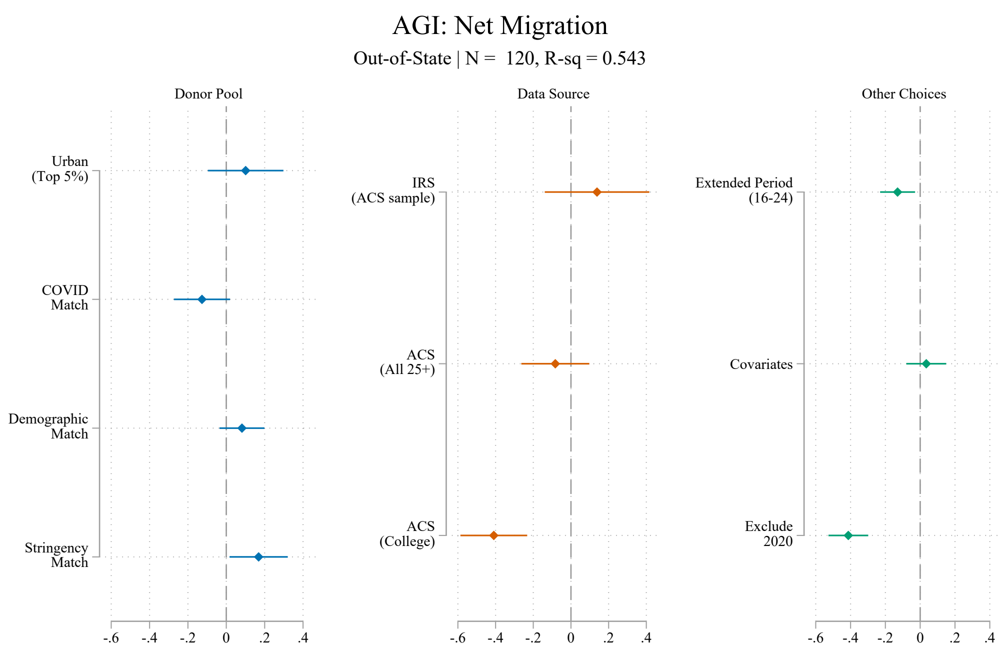
(b) Oregon state revenue loss

Notes: Distribution of estimated revenue effects obtained by applying each SDID specification's migration estimate to the microsimulation tax model. Panel (a) shows the distribution of PFA revenue losses ($ millions); panel (b) shows the distribution of Oregon state income tax revenue losses ($ millions). Dashed vertical lines mark the four highlighted benchmark specifications; vermillion lines denote IRS-based estimates and blue lines denote ACS College estimates. Source: Authors' calculations.

Figure 15: Specification Influence: What Drives Variation in AGI Net In-Migration Estimates?



(a) Inter-county



(b) Interstate

Notes: Meta-regression decomposition of specification curve estimates for the AGI net in-migration effect. Each bar shows the estimated coefficient from a regression of the specification-level SDID estimate on indicator variables for each modeling choice (data source, donor pool, covariates, exclusion of 2020). Positive values indicate that the choice is associated with a more positive (less negative) net in-migration estimate. Panel (a): inter-county migration. Panel (b): interstate migration. Source: Authors' calculations.

Appendix A Additional Results

Table A1: County-Level Migration Rates: Multnomah vs. National Distribution

	2018–2019				2021–2022			
	Mult.	Median	25th	75th	Mult.	Median	25th	75th
Returns								
Out-migration	8.50	6.19	5.36	7.20	9.67	6.38	5.46	7.37
In-migration	8.76	6.06	4.89	7.69	8.50	6.73	5.40	8.51
Net migration	0.26	-0.12	-0.66	0.57	-1.18	0.33	-0.32	1.22
Exemptions								
Out-migration	7.38	5.59	4.73	6.54	8.62	5.63	4.73	6.59
In-migration	6.91	5.57	4.40	7.08	6.72	6.06	4.82	7.78
Net migration	-0.47	0.00	-0.53	0.69	-1.91	0.44	-0.22	1.36
AGI								
Out-migration	7.01	4.89	4.18	5.78	9.69	4.99	4.18	5.96
In-migration	6.59	4.83	3.74	6.49	6.29	5.54	4.11	7.74
Net migration	-0.42	-0.07	-0.70	0.93	-3.40	0.49	-0.39	1.94

Notes: Migration rates as a percentage of the base filing population (non-movers plus all movers). Pre-period averages 2018–2019; post-period averages 2021–2022. Distribution statistics computed across all U.S. counties excluding Multnomah. Source: IRS Statistics of Income.

Table A2: State-Level Migration Rates: Oregon vs. National Distribution

	2018–2019				2021–2022			
	Oregon	Median	25th	75th	Oregon	Median	25th	75th
Returns								
Out-migration	3.56	3.22	2.86	3.86	4.17	3.53	3.02	4.00
In-migration	4.29	3.41	2.65	4.22	4.15	3.75	2.86	4.62
Net migration	0.73	-0.08	-0.45	0.48	-0.02	0.07	-0.30	0.79
Exemptions								
Out-migration	3.02	2.84	2.48	3.31	3.68	3.00	2.56	3.54
In-migration	3.56	2.96	2.25	3.69	3.42	3.31	2.45	4.15
Net migration	0.54	-0.05	-0.36	0.47	-0.26	-0.03	-0.27	0.73
AGI								
Out-migration	3.02	2.79	2.45	3.36	3.93	3.14	2.68	3.83
In-migration	3.65	2.70	2.07	3.83	3.72	3.27	2.29	4.95
Net migration	0.63	-0.21	-0.50	0.72	-0.21	-0.01	-0.58	1.45

Notes: Migration rates as a percentage of the base filing population (non-movers plus all movers). Pre-period averages 2018–2019; post-period averages 2021–2022. Distribution statistics computed across all U.S. states excluding Oregon. Source: IRS Statistics of Income.

Table A3: Difference-in-Differences Regression Results

	(1) Out-migration	(2) Out-of-state	(3) In-migration (West Coast)	(4) In-migration (Lower 48 + DC)
Panel A: College Degree as Treatment Proxy				
College Degree × Post	2.129***	1.522***	-0.003	-0.002
	(0.514)	(0.401)	(0.011)	(0.002)
Panel B: Age Group as Treatment Proxy (Reference: 45–64)				
Age 25-44 × Post	-0.090	-0.325	-0.022	-0.004*
	(0.584)	(0.460)	(0.014)	(0.002)
Age 65+ × Post	-1.145**	-0.949***	-0.001	0.000
	(0.503)	(0.353)	(0.007)	(0.001)
Panel C: Treatment heterogeniety by age (College × Age × Post)				
College × Post × Age 25-44	2.408***	1.888***	0.009	0.002
	(0.702)	(0.574)	(0.015)	(0.003)
College × Post × Age 45-64	2.381***	1.912***	-0.009	-0.005**
	(0.633)	(0.506)	(0.014)	(0.002)
College × Post × Age 65+	0.863	-0.244	-0.016	-0.007**
	(0.612)	(0.367)	(0.013)	(0.003)
Observations	58,727	58,727	3,585,562	23,638,195

Standard errors in parentheses

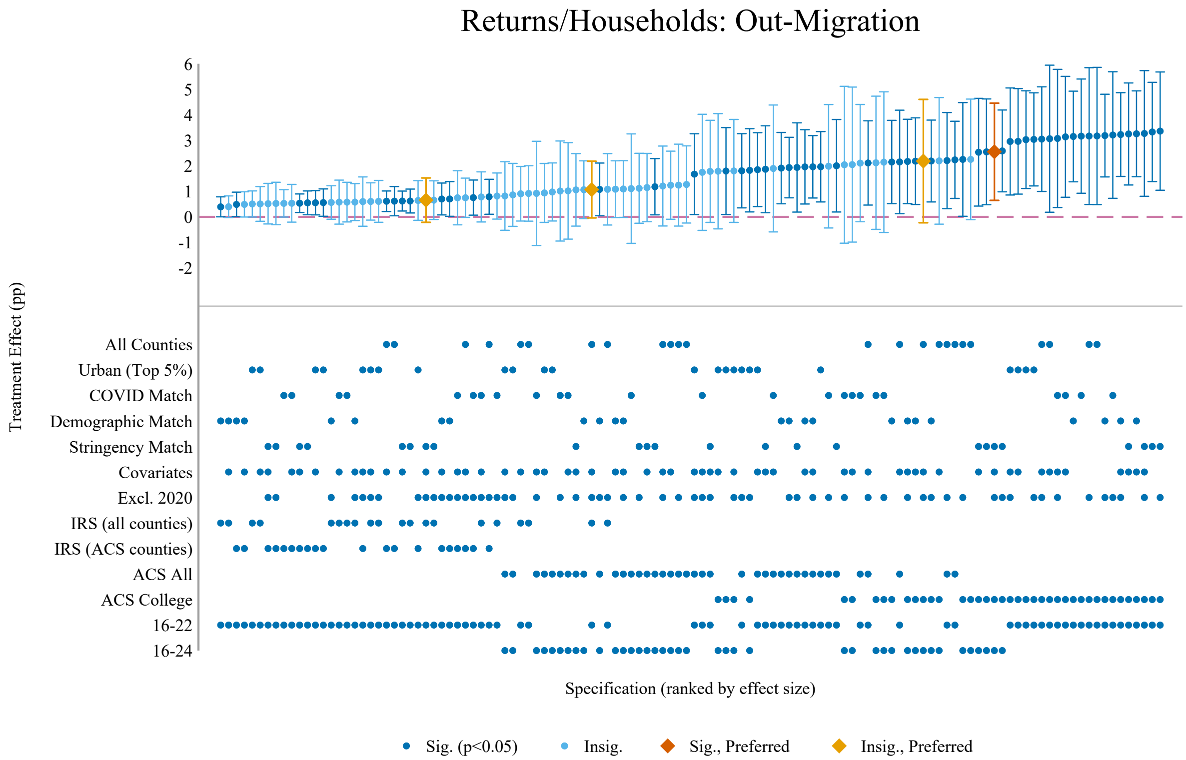
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Panel A reports the coefficient on College Degree × Post from Equation (5). Panel B reports Age Group × Post coefficients with 45–64 as the omitted reference group. Panel C reports the triple-interaction College × Post × Age Group. Columns (1)–(2) estimate out-migration from Multnomah County (any county move and out-of-state move, respectively). Columns (3)–(4) estimate in-migration to Multnomah County (West Coast and lower 48 + DC samples, respectively). All specifications include year fixed effects and categorical controls (age, sex, marital status, children, education). In-migration models include origin county fixed effects. Standard errors: robust for out-migration, clustered by origin county for in-migration. Sample: ACS 2016–2024, ages 25+, excluding 2020. Source: Authors' calculations.

Table A4: Observation Counts by Sample and Data Source

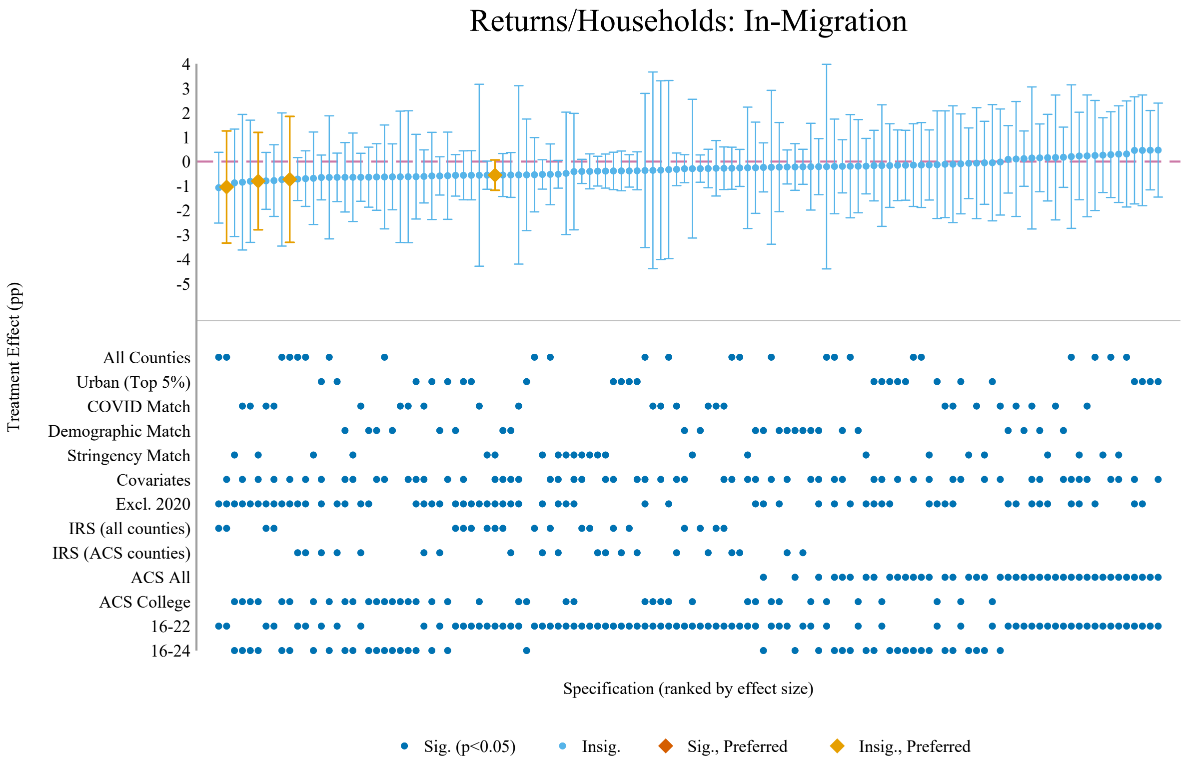
Approach	Sample	Data	Unit	Units	Years	
DiD	In-migration (Lower 48)	ACS (individual)	person-year	23,638,195	11	23,
DiD	In-migration (West Coast)	ACS (individual)	person-year	3,585,562	11	3,5
DiD	Out-migration (Multnomah)	ACS (individual)	person-year	58,727	11	
Flows	All	IRS	flow-year	71,064	7	3
Narrow SDID	22-county pool	IRS	county-year	22	7	
SDID	All counties	ACS (2016–2022)	county-year	389	7	
SDID	All counties	ACS (2016–2024)	county-year	389	9	
SDID	All counties	IRS	county-year	3,079	7	
SDID	Urban (p95)	IRS	county-year	154	7	

Figure A1: SDID Specification Curves: Returns/Households Migration Rates
(a) Out-Migration



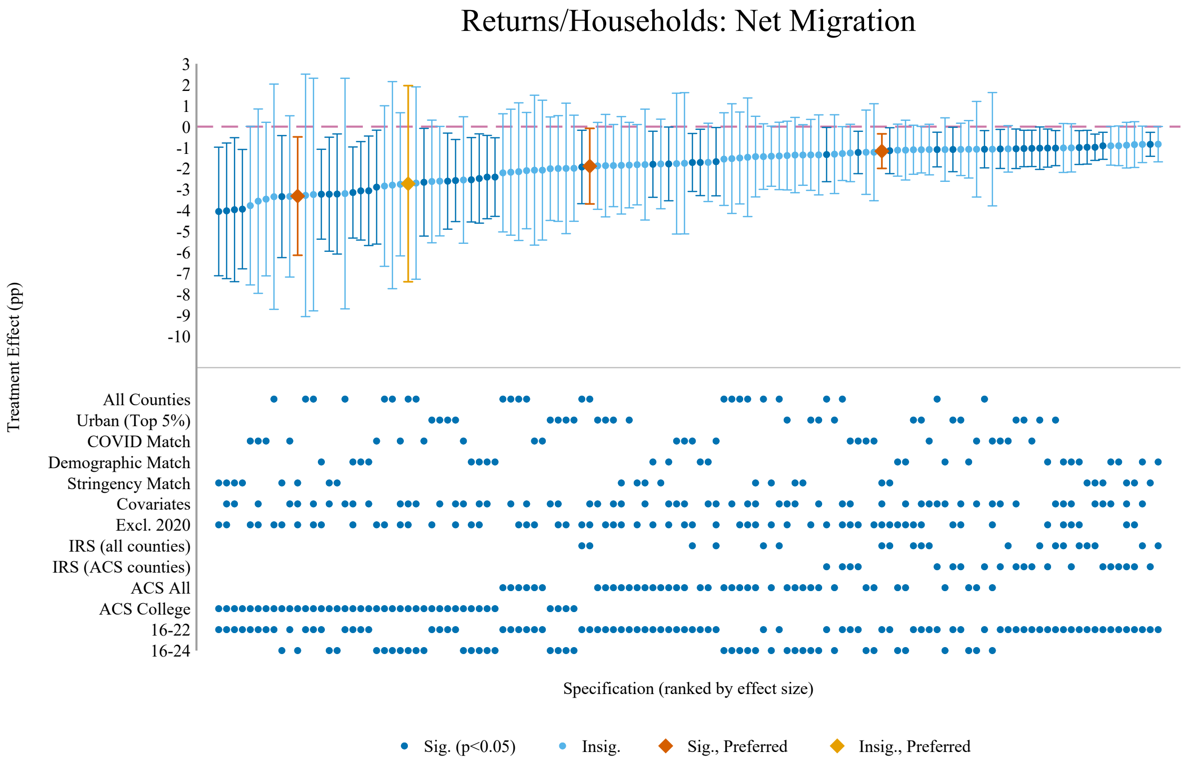
Notes: Each point represents a separate SDID estimate of the effect of PFA on the returns (IRS) or households (ACS) out-migration rate from Multnomah County. See notes to Figure 4 for specification details. Source: Authors' calculations using IRS SOI data and ACS microdata.

Figure A1: SDID Specification Curves: Returns/Households Migration Rates
(b) In-Migration



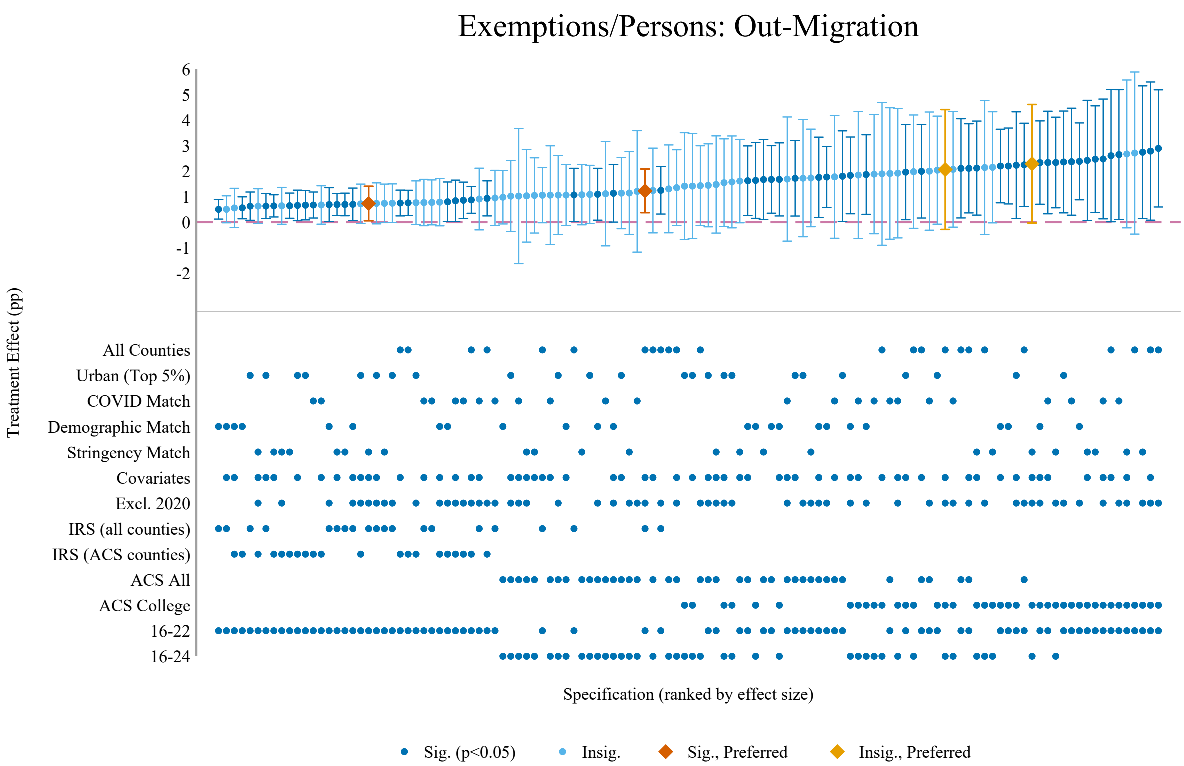
Notes: See notes to panel (a). Outcome is the returns/households in-migration rate to Multnomah County.

Figure A1: SDID Specification Curves: Returns/Households Migration Rates
(c) Net In-Migration



Notes: See notes to panel (a). Outcome is the returns/households net in-migration rate for Multnomah County.

Figure A2: SDID Specification Curves: Exemptions/Individuals Migration Rates
(a) Out-Migration

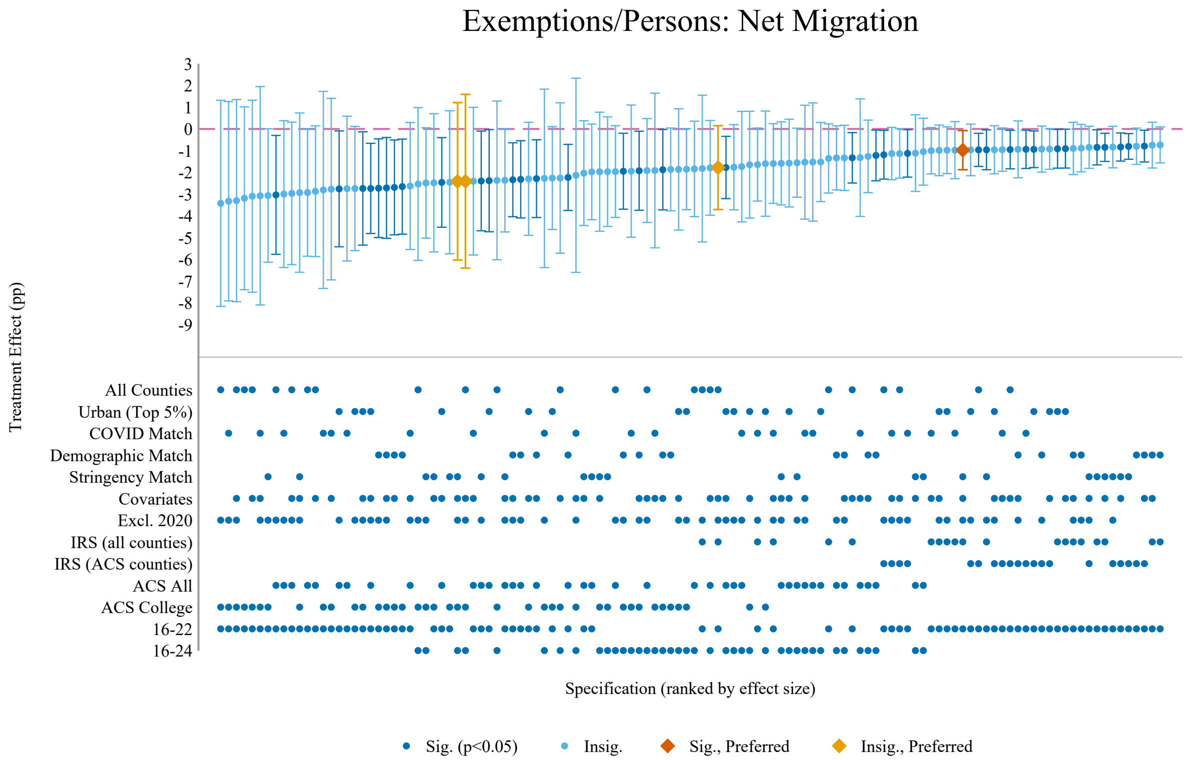


Notes: Each point represents a separate SDID estimate of the effect of PFA on the exemptions (IRS) or individuals (ACS) out-migration rate from Multnomah County. See notes to Figure 4 for specification details. Source: Authors' calculations using IRS SOI data and ACS microdata.

Figure A2: SDID Specification Curves: Exemptions/Individuals Migration Rates
(b) In-Migration

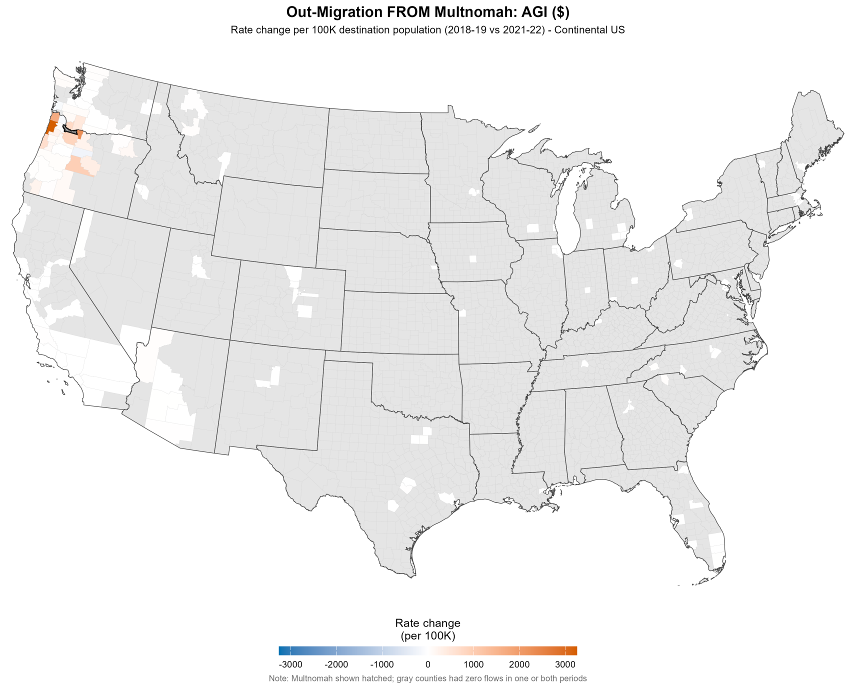
Notes: See notes to panel (a). Outcome is the exemptions/individuals in-migration rate to Multnomah County.

Figure A2: SDID Specification Curves: Exemptions/Individuals Migration Rates
(c) Net In-Migration



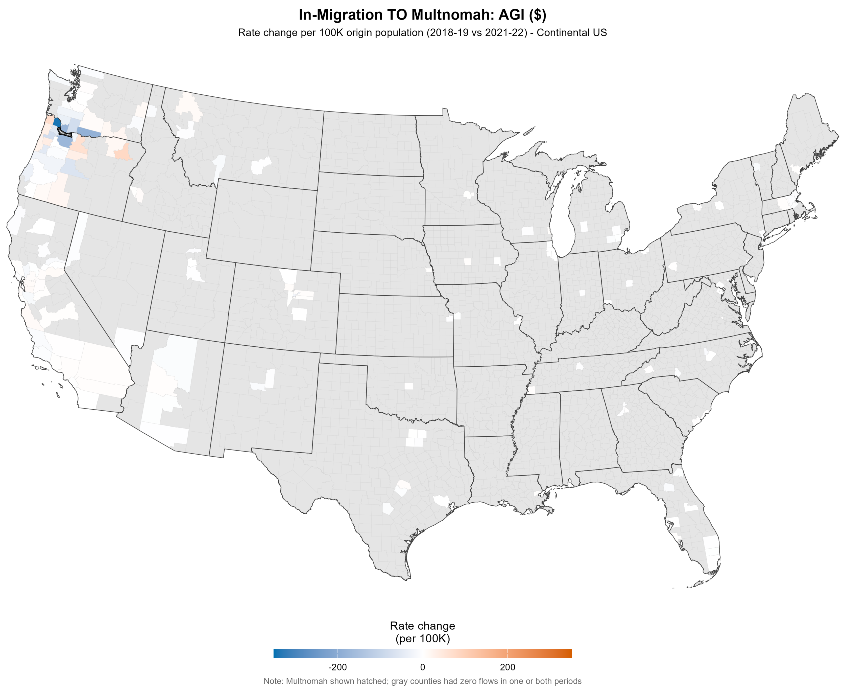
Notes: See notes to panel (a). Outcome is the exemptions/individuals net in-migration rate for Multnomah County.

Figure A3: Change in AGI Outflows from Multnomah County After PFA (Full U.S.)



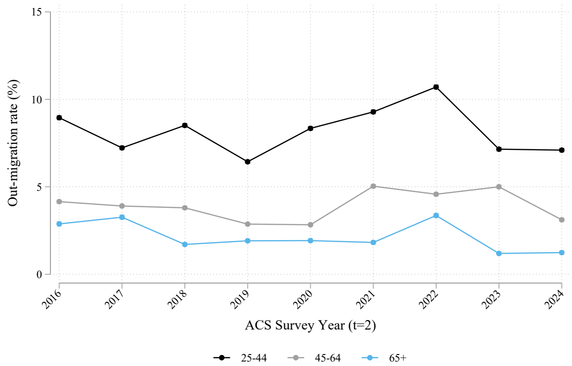
Notes: See notes to Figure 7. This figure shows all U.S. counties rather than only the Pacific Northwest. Source: Authors' calculations using IRS SOI county-to-county flow data.

Figure A4: Change in AGI Inflows to Multnomah County After PFA (Full U.S.)

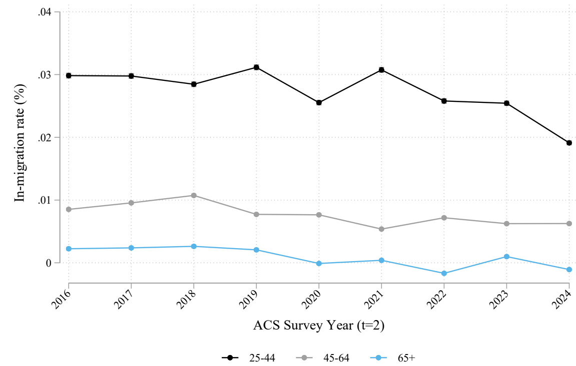


Notes: See notes to Figure 8. This figure shows all U.S. counties rather than only the Pacific Northwest. Source: Authors' calculations using IRS SOI county-to-county flow data.

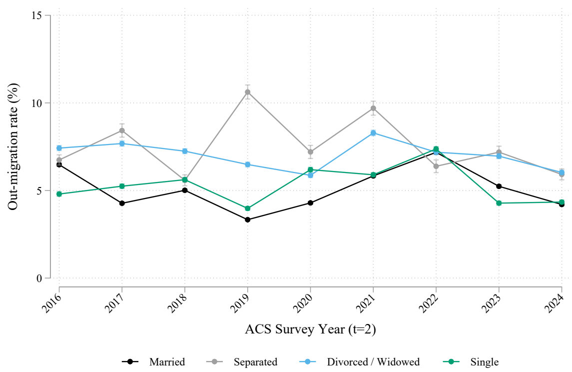
Figure A5: Conditional Mean Migration Rates by Additional Characteristics



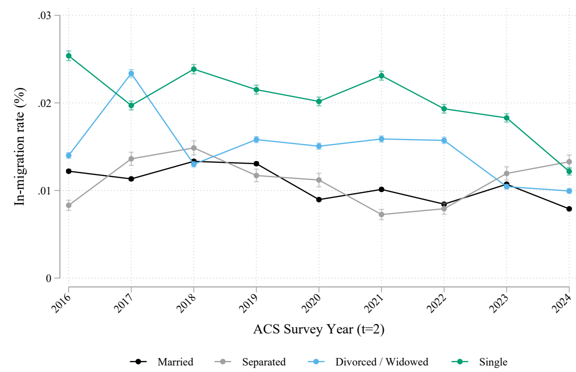
(a) Out-migration by age



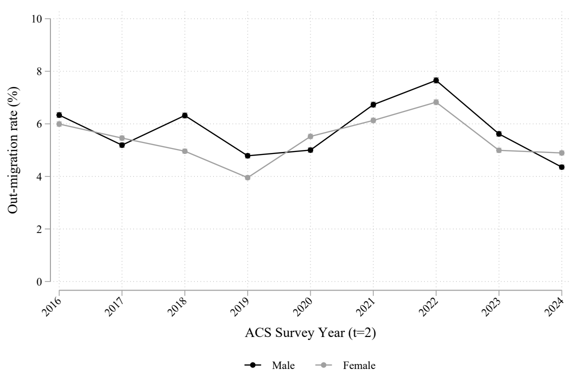
(b) In-migration by age



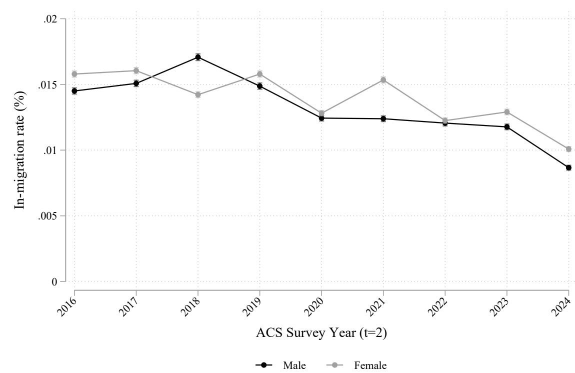
(c) Out-migration by marital status



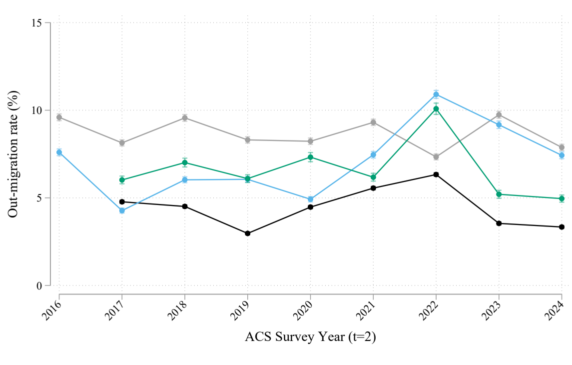
(d) In-migration by marital status



(e) Out-migration by sex



(f) In-migration by sex



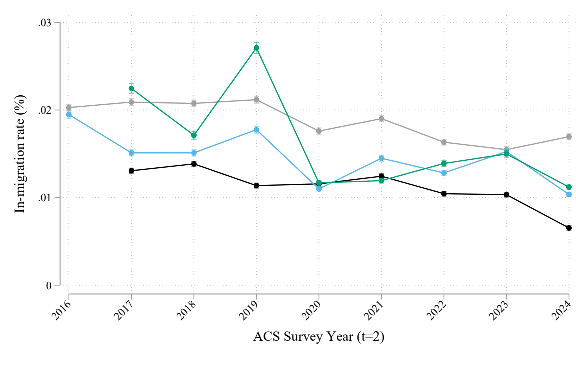
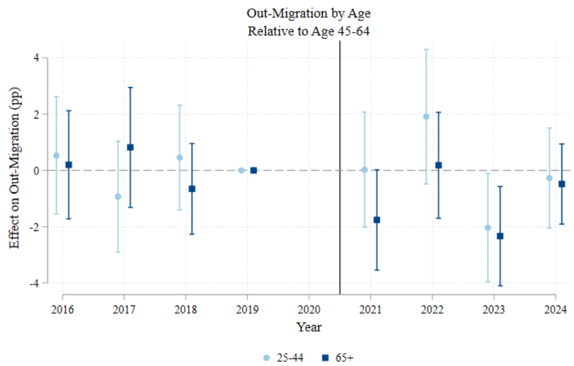
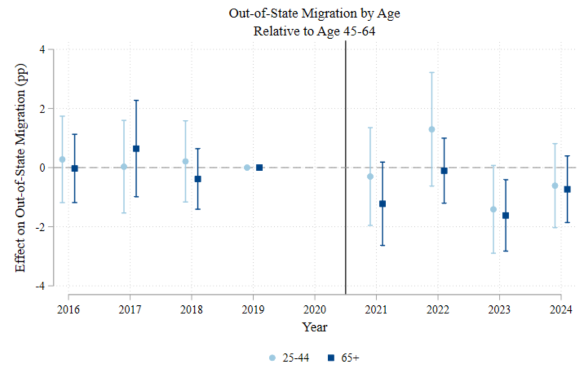


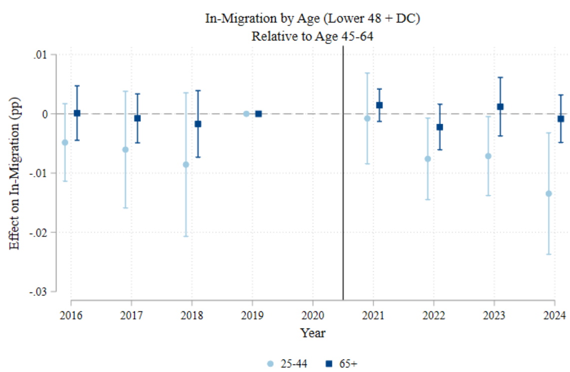
Figure A6: DiD Event Studies: Triple-Difference (College × Age × Post)



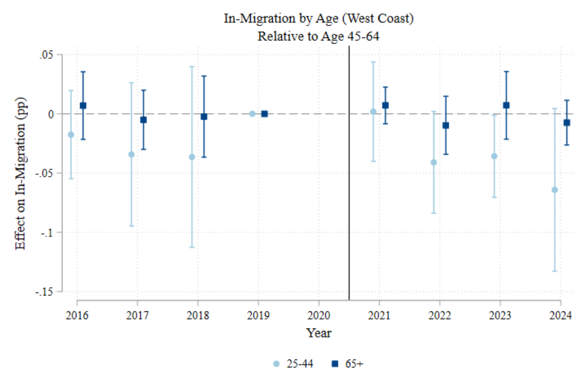
(a) Out-migration, any county move



(b) Out-migration, out-of-state move



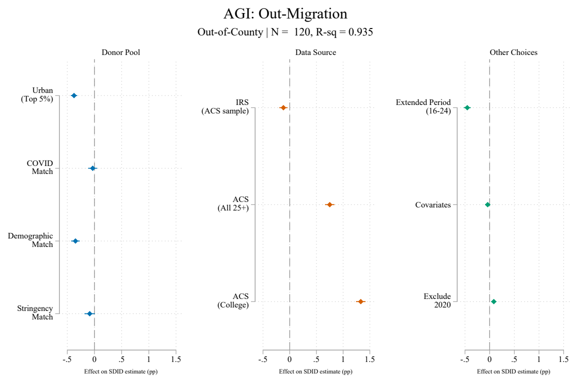
(c) In-migration, lower 48 + DC



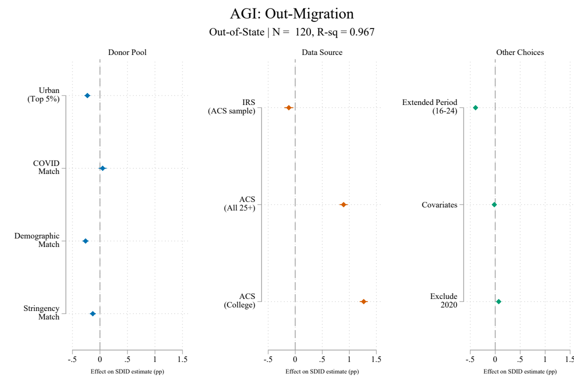
(d) In-migration, CA/OR/WA

Notes: Event study estimates from a triple-difference specification interacting college education, age group, and year indicators. Top row: out-migration from Multnomah County (left: any county move; right: out-of-state move). Bottom row: in-migration to Multnomah County (left: lower 48 + DC sample; right: CA/OR/WA sample). Reference group: non-college-educated, ages 45–64, in 2019. Year 2020 is excluded. All specifications include year fixed effects and categorical controls. In-migration models include origin county fixed effects. Whiskers show 95% confidence intervals. Source: Authors' calculations using ACS microdata (2016–2024). Sample: ages 25+.

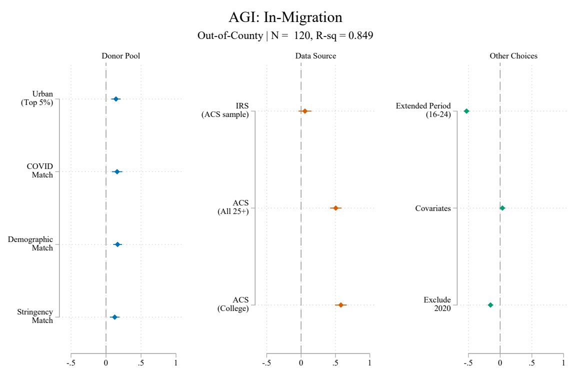
Figure A7: Specification Influence: AGI Out- and In-Migration Estimates



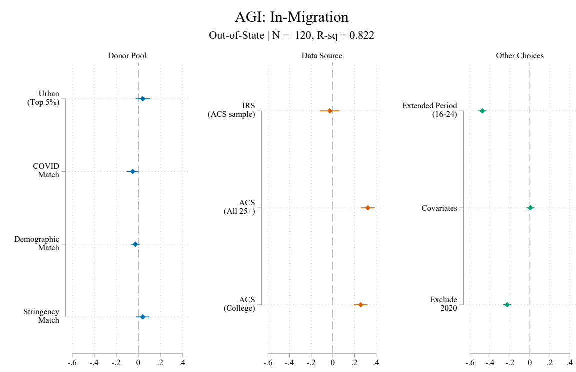
(a) Out-migration, county



(b) Out-migration, interstate



(c) In-migration, county



(d) In-migration, interstate

Notes: Meta-regression decomposition of specification curve estimates for AGI out-migration (top row) and in-migration (bottom row) effects. Left column: inter-county migration. Right column: interstate migration. See notes to Figure 15. Source: Authors' calculations.

Appendix B IRS Migration Data Quality

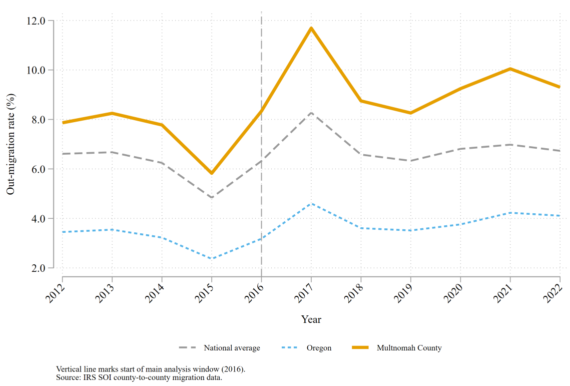
DeWaard et al. (2022) document a period of anomalous volatility in the public-use IRS migration data following the IRS's takeover of data processing from the Census Bureau in 2011–12. The anomaly manifests as an unusually steep decline in gross rates from 2012–13 to 2014–15 (to levels below the Great Recession trough), followed by a dramatic increase peaking in 2016–17 (the highest recorded rate since 1990–91), and a sharp reversal in 2017–18. Crucially, DeWaard et al. show that the anomaly is *uniform* across all Census regions, metropolitan/nonmetropolitan quartiles, and income quartiles. Net migration rates are less affected because the in- and out-migration fluctuations largely offset.

While the authors of that paper outline several potential causes of these data issues (mainly stemming from changes in data processing after 2011) separate work we have conducted within the IRS leads us to believe the issue is caused by a more fundamental data issue, whereby certain addresses have been overwritten within the IRS data files. The exact nature of this data issue will be the subject of future work.

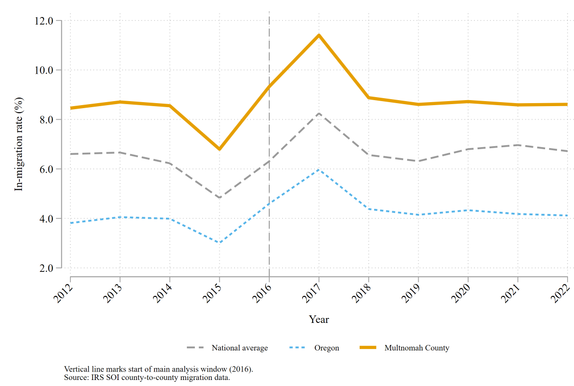
Our IRS analysis covers tax years 2016 through 2022 (representing 2015–16 through 2021–22 flows). The pre-treatment period (2016–2019) therefore overlaps only with the tail end of the anomaly—the 2016–17 peak and 2017–18 decline. To assess whether this overlap poses a threat to our identification strategy, we extend the IRS data back to 2012 (the 2011–12 flows) to observe the full anomaly period and examine whether Multnomah County was differentially affected. Critically, the presence of this error will not introduce bias into our estimate if Multnomah County is not differentially affected by this error. One comforting feature of our analysis is that the results are consistent across both IRS and ACS data, but it is still worth investigating the nature and scope of this error.

Figure B1 plots the inter-county out- and in-migration rates for Multnomah County alongside the national county average and Oregon state-level rates from 2012 through 2022. Both panels show the characteristic pattern documented by DeWaard et al. (2022): a decline in gross rates through the mid-2010s, a peak around 2016–17, and a subsequent decline. Multnomah County tracks the national and state patterns closely, with no evidence of differential behavior during the anomalous years. The vertical dashed line at 2016 marks the start of our analysis window; some of the most volatile years (2013–2015) are excluded from our main specifications entirely.

Figure B1: Inter-county Out- and In-Migration Rates: National Average, Oregon, and Multnomah County



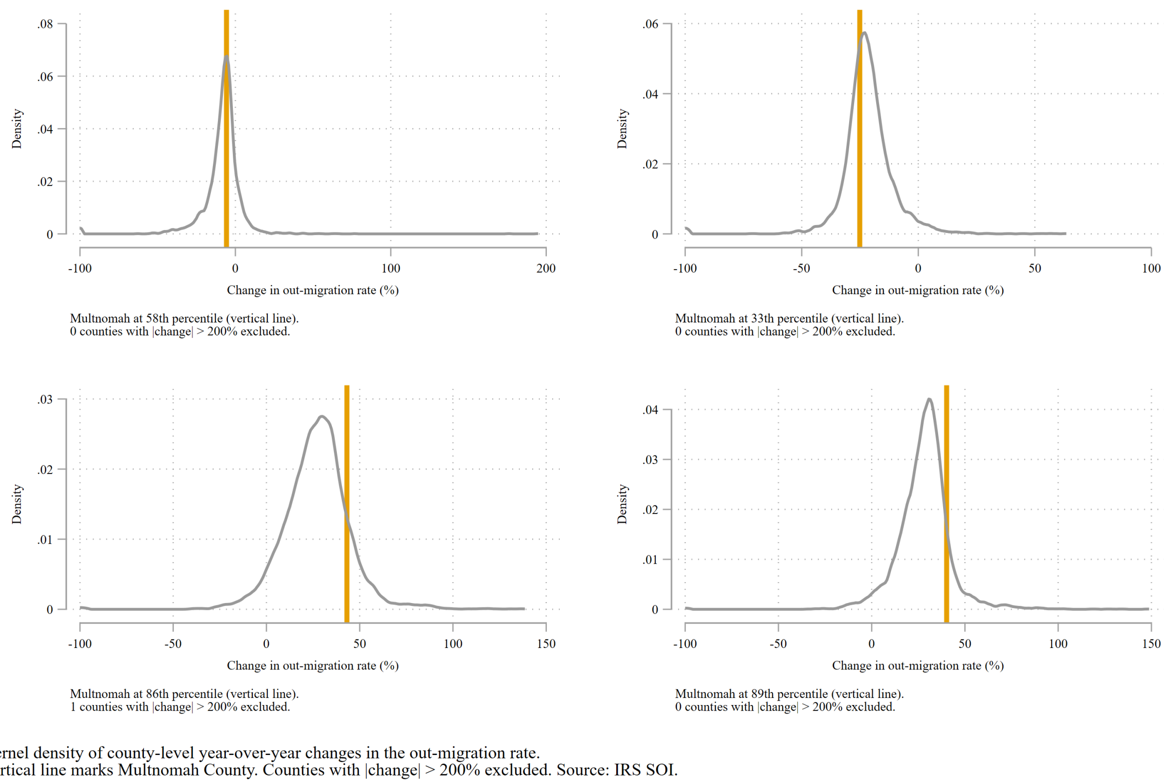
(a) Out-migration rate



(b) In-migration rate

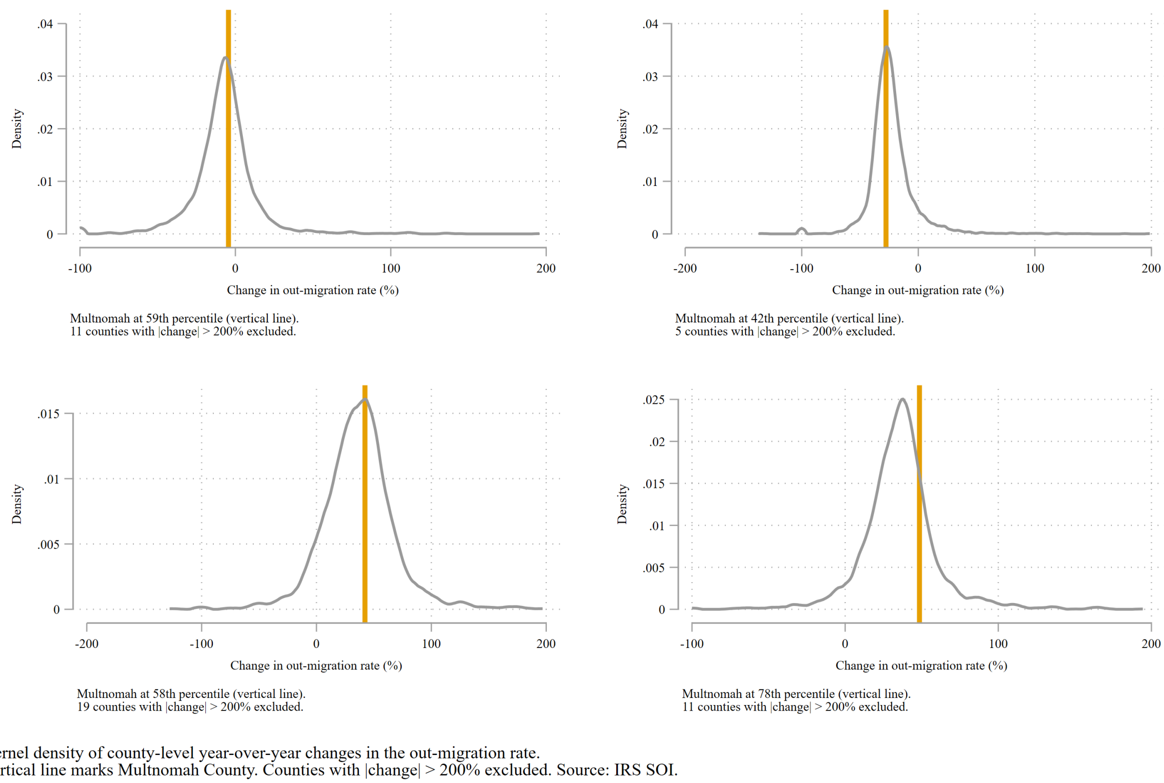
Notes: Inter-county out-migration rate (panel a) and in-migration rate (panel b), measured as inter-county mover returns divided by total returns (stayers plus all movers), 2012–2022. Gray dashed line: population-weighted mean across all U.S. counties. Navy short-dashed line: Oregon. Red solid line: Multnomah County. Vertical dashed line marks the start of the main analysis window (2016). Source: Authors' calculations using IRS SOI county-to-county migration data.

Figure B2: Distribution of Year-over-Year Changes in Out-Migration Rate (Returns)



Notes: Each panel shows the kernel density of county-level year-over-year changes in the inter-county out-migration rate (returns), with Multnomah County marked by a red vertical line. Panels correspond to the four transition years spanning the IRS data anomaly period. The percentile rank of Multnomah County within the cross-county distribution is reported in each panel. Source: Authors' calculations using IRS SOI county-to-county migration data.

Figure B3: Distribution of Year-over-Year Changes in Out-Migration Rate (AGI)



Notes: Each panel shows the kernel density of county-level year-over-year changes in the inter-county out-migration rate (AGI), with Multnomah County marked by a red vertical line. Panels correspond to the four transition years spanning the IRS data anomaly period. The percentile rank of Multnomah County within the cross-county distribution is reported in each panel. Source: Authors' calculations using IRS SOI county-to-county migration data.

Figures B2 and B3 provide a more formal test. For each anomalous transition year, we compute the year-over-year percent change in the out-migration rate for every U.S. county and plot the resulting cross-county distribution. Multnomah County's position is marked with a vertical line. Across both measures, for most years, Multnomah County falls well in the middle of the distribution. For the most recent year of volatility, Multnomah is higher up the distribution, but not unreasonably so. This confirms that the IRS processing anomaly did not differentially affect Multnomah County.

These results support the validity of our SDID approach, which identifies treatment effects from *relative* differences between Multnomah County and a synthetic control group. Because the IRS data anomaly affected Multnomah County and its potential control counties similarly, the noise it introduces is common across units and does not bias the estimated treatment effect. It may reduce precision in the pre-treatment period, but this is a conservative concern (attenuation, not bias).