Does State Tax Reciprocity Affect Interstate Commuting? Evidence from a Natural Experiment*

Gary A. Wagner† and Jonathan C. Rork‡

June 2023

Abstract

This paper exploits the 2010 dissolution of the personal income tax reciprocity agreement between Minnesota and Wisconsin to estimate how state tax policies affect interstate commuting. This policy shock increased tax liability for some commuters and tax compliance costs for all commuters. Using a synthetic control approach designed for panel data, we compare the interstate commuting behavior of Wisconsinites and Minnesotans to unaffected intrastate commuters who live and work in the same state, intrastate commuters who live in other large metro areas, and several multi-state metro areas in other states where income tax reciprocity remained intact. Post-dissolution, we find robust evidence that the number of interstate commuters in Wisconsin border counties falls between 3 and 5%, with stronger declines found for younger and middle-income workers.

Keywords: commuting, reciprocity, state taxation, synthetic control method
JEL Classification Numbers: H7, R5

*This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. We thank Brantly Callway, Tim Komarek, Luke Watson, Jinwom Kim, and seminar participants at the 2021 Eastern Economic Association Conference for a number of valuable suggestions that have improved the paper. We are also grateful to Eli Ben-Michael for answering questions about the partially pooled synthetic control method, and to Timothy P. Noonan, Esquire for answering legal questions about state tax credits. Finally, we thank Editor Laurent Gobillon and two anonymous referees. Any errors are our own.

†Acadiana Business Economist Endowed Chair and Professor of Economics, University of Louisiana at Lafayette, Email: gary.wagner@louisiana.edu.

‡George Hay Professor of Economics, Reed College, Email: jrork@reed.edu.

1 Introduction

In October 2020, Massachusetts enacted what was known as a temporary convenience rule, whereby it taxed work performed by employees of Massachusetts-based companies regardless of where the work was performed. Because this disproportionately impacted residents of southern New Hampshire, the state of New Hampshire filed suit against Massachusetts (*New Hampshire v Massachusetts*) arguing this was an extraterritorial assertion of taxation. The US Supreme Court chose not to review the case, and the temporary rule was later rescinded as the pandemic improved.

Like many states, Massachusetts taxes wage income at the place of employment, rather than the place of residence. With its non-resident workforce no longer entering the state due to stay-at-home orders under Covid-19, the state faced a budgetary shortfall. As a result, Massachusetts invoked the rule in order to recoup this revenue. With Boston being a multistate MSA, this example highlighted the importance of out of state commuters to Massachusetts. The state is not alone, as there are many other states (e.g. Oregon, New York, Missouri, Ohio) that are home to a multistate MSA and hence have budgets influenced by non-resident employees.

One way for states to limit said impact is to enter into an income tax reciprocity agreement. These bilateral agreements allow income to be taxed in the state of residence, even though it is earned in another state. Currently, 15 states, primarily located in the Midwest and Mid-Atlantic, are engaged in over 50 such agreements (Rork and Wagner 2012). While reciprocity agreements are thought of as primarily addressing double taxation concerns of residents, the Massachusetts case highlights how reciprocity agreements could provide for a more stable income tax base that is not reliant on the flows of non-resident commuters.

As highlighted in Rork and Wagner (2012), the majority of existing reciprocity agreements were enacted in the 1970's, and once they were put in place, they tend to stay in place. Hence, it is difficult to ascertain the role reciprocity agreements play in promoting interstate commuting. Fortunately, we are able to exploit a natural experiment in which Minnesota and Wisconsin repealed their personal income tax reciprocity agreement in 2010. This policy shock increased tax liability for some commuters and increased tax compliance costs for all interstate commuters. To estimate interstate commuters' responsiveness to this shock, we leverage the long-term stability of their tax treatment status and rely on a wide range of comparison groups as robustness checks.

The majority of interstate commuters live in, or near, one of the three multi-state metropolitan statistical areas that span the border. Three quarters of the states' interstate commuters live in Wisconsin and work in Minnesota. To explore the causal effect of repealing reciprocity, we pursue a synthetic control approach designed for panel data settings, comparing the interstate commuting behavior of Wisconsinites and Minnesotans to unaffected intrastate commuters who live and work in the same county, unaffected intrastate commuters who live and work in the same state, and several multi-state metro areas in other states where income tax reciprocity remained intact.

Our findings show that repealing tax reciprocity had an economically meaningful and lasting effect on interstate commuting. Specifically, the number of commuters from Wisconsin census tracts bordering Minnesota fell by an average of 3-5%. Notably, the effects are heterogeneous by earnings, with commuters earning between $1250 and $3333 per month being the most sensitive. Workers ages 29 and younger were also found to be the most sensitive to repealing reciprocity. The results for Minnesotans are less clear, which is consistent with the importance of interstate tax differentials and income distributions of interstate commuters.

2 Commuting and Reciprocity

2.1 Literature Review

Traditional urban economic models in the spirit of Alonso-Mills-Muth recognize that workers make tradeoffs when considering housing choices and commutes (Alonso 1960; Alonso 1964; Mills 1967; Mills 1972; Muth 1969). All things equal, workers prefer to minimize their commute; however, they are willing to trade longer commutes for more affordable housing (Levinson 1997; Plaut 2006; Hanson 2012), helping to create a negatively sloped residential bid-rent function. Since workers' heterogeneous preferences for housing also incorporate factors such as schools, parks, and other amenities (Albouy and Lue 2015), the distance-housing price tradeoff may be non-linear.

Workers with the ability to work from home typically live farther from employers but, because they commute less frequently, travel fewer miles to work and spend less time and money on that travel (Mokhtarian et al. 2004; Zyu 2013; Vos et al. 2018). This flattens the residential bid-rent function and strengthens the relative importance of amenities over distance to work in determining where to live. Recent evidence also suggests that shorter commutes are associated with higher levels of self-reported satisfaction (Simón et al. 2020).

How does taxation enter the picture? Most commuting studies focus on metropolitan areas (Kim 1995, Levinson 1997, Raphael 1998, Hewings et al. 2001, Gottlieb and Lentnek 2001, Horner and Murray 2003, Lee 2007), typically limiting the examination of taxes to housing affordability, such as property taxes or mortgage interest deductions (e.g. Hanson 2012, Hanson and Martin 2016). Personal income taxes also become potentially important for interstate commuter flows because of their influence on workers' take-home wages and housing budgets.

Of particular interest is the situation of workers who reside in one state and work in another, therefore potentially subjecting themselves to a greater risk of double taxation (Holcomb 2008; Hellerstein et al. 2011). According to Hellerstein et al. (2011), this is because the U.S. Supreme Court has affirmed that a state has the authority to tax residents on all their personal income (wherever derived) *and* the authority to tax non-resident income earned within their state. One important caveat, however, is a concept that legal scholars refer to as the "dormant or negative" Commerce Clause doctrine of the U.S. Constitution (Knoll and Mason 2017). Since the Commerce Clause grants Congress the explicit authority to regulate interstate commerce, this implicitly limits the authority of states to tax or regulate economic activity if doing so would create an unreasonable burden on interstate commerce (Knoll and Mason 2017). In other words, states have the legal authority to tax non-resident income (earned in their state) insofar as those actions are deemed not to "unreasonably burden" interstate commerce.

The standard of what constitutes an unreasonable burden depends on the specific facts and circumstances of each case before the courts. States have largely managed to avoid legal challenges on issues related to taxing non-resident income by offering credits to their residents for income taxes paid in other states (Rork and Wagner 2012). States generally offer credits up to the maximum liability that would be owed in the home state. For example, suppose an individual lives in State A and works in State B. Their employer in State B would withhold income tax to cover State B's tax liability. Assume this amount is $2,000. Suppose, hypothetically, that this individual's tax liability would be $3,500 if they lived and worked in State A. Under a credit system, State A would reduce this individual's home state tax liability up to a maximum of $2,000, thereby lowering their home state tax liability from $3,500 to $1,500.

While a credit system has distributional implications for the tax revenue, there are other drawbacks as well. Taxpayers living and working in different states are required to file returns in their state of residence and state of employment. Further complicating matters, states only offer credits on income that is subject to tax based on their own sourcing rules (Noonan and Pascal 2012). This means that if States A and B have different tax bases, the home state's resident credit may not fully offset work state taxes even if the tax rates are equivalent between the states. Said differently, a credit system is only revenue neutral for taxpayers and states if the home and work states have identical income tax systems.[1]

A select group of states, however, have entered into formal bilateral income tax reciprocity agreements as an alternative to the credit system. This results in income being taxed as though it were earned in the state of residence, as opposed to the state of employment. States in a reciprocity agreement agree not to withhold tax for their state from the employee, although many will withhold for the state of residence out of courtesy. In addition to shifting withholding requirements for employers, reciprocity agreements eliminate any risk of double taxation for taxpayers, disincentivize member states from altering their income tax bases to target non-residents, and reduce compliance costs down to a single tax return (in the state of residence).[2]

Reciprocity agreements are most common between neighboring states in the Midwest and Northeast, probably because these states tend to be both heavily populated and to have geographically close out-of-state urban areas. Kentucky and Virginia formed the first reciprocity agreement in 1964; currently more than 30 agreements are in place amongst 15 states (Rork and Wagner 2012).

As Rork and Wagner (2012) discussed, since participation in a reciprocity agreement is voluntary, both parties must view an agreement to be beneficial, or least not harmful, for the agreement to endure. That said, there are several reasons a state may enter into such an agreement. First, low tax rate areas and states that are net losers of commuters may have an incentive to exclude non-residents to attract new residents and new jobs (Bruce et al. 2014). Next, granting reciprocity significantly reduces the administrative and monitoring costs associated with taxing non-residents. Finally, as labor and capital have become more mobile over time, states may enact reciprocity agreements because they fear a race-to-the-bottom with neighboring states that could erode their

[1] Double taxation is also possible because of differences in how states define residents. If an individual meets the residency requirements of more than one state, then non-sourced income, such as investment income, can be subject to taxation in both states (assuming it is part of both state's personal income tax base).

[2] It would not be legal for a state to expand its income tax base and only tax non-residents on a source of income earned in their state. However, if an expanded tax base applied to residents and non-residents, then such a tax would be legal.

tax base.

Reciprocity agreements could incentivize interstate commute flows via several mechanisms. First, reciprocity may impact firm location and, indirectly, affect commuting behavior. As discussed by Braid (2000), states that engage in tax competition for business will utilize a source-based wage tax (as opposed to a capital tax) when possible. The reciprocity agreement effectively eliminates such use for competition, leading to greater cooperation amongst states that are parties to such an agreement (Rork and Wagner 2012). As economies become more interregional (Hewings et al. 2001; Renkow 2006), this cooperation may result in states taking a regional approach to attracting firms, resulting in a virtuous circle of more firms, more workers, and an expanded tax base for all.

Reciprocity may also directly influence interstate commute flows through multiple channels. First, these agreements reduce the costs of tax compliance. Workers of both states no longer have to navigate two sets of income tax forms nor try to weave their way through a system of credits. This lowers commuting costs for non-residents. Second, reciprocity agreements shift taxes from the state of employment to the state of residence. If tax liability is higher in the state of employment, reciprocity may lower the tax burden for these interstate commuters. If, alternatively, the tax liability is lower in the state of employment, reciprocity may be neutral (to an individual taxpayer) from a tax burden perspective under a system of fully offsetting credits. The net fiscal effect on each state will depend on the net flow of interstate commuters, earnings profiles of those commuters, and the income tax base sourcing rules of each state.

Work by Coomes and Hoyt (2008) and Agrawal and Hoyt (2018) show that people are sensitive to reciprocity agreements when locating into a multi-state MSA; Rohlin et al. (2014) find firms show similar sensitivity. Because reciprocity agreements tend to remain in place for decades, our study is unique - the first to focus on such an agreement's dissolution. Likewise, our study is the first to shed light on whether these agreements remain salient even after workers and firms have settled in a region.

2.2 The History of Minnesota-Wisconsin Income Tax Reciprocity

In 1968, Minnesota and Wisconsin entered into an income tax reciprocity agreement. This agreement would be the first of three for Minnesota and the third of five for Wisconsin. In 2009, Minnesota cancelled the agreement, only the second cancellation of a reciprocity agreement in the

United States. We outline the history of the Minnesota-Wisconsin agreement below.[3]

Minnesota Statue 290.081 provides the Commissioner of Revenue the authority to enter into income tax reciprocity agreements with other states. The Commissioner is given the ability to cancel an agreement should it be in the state's best interest. Minnesota and Wisconsin signed their agreement in 1967, effective in 1968. By 1973, the number of Wisconsin residents working in Minnesota began to exceed the number of Minnesota residents working in Wisconsin. Minnesota Governor Wendell Anderson proposed repealing all income tax reciprocity agreements because of the revenue loss the imbalance was causing Minnesota. His proposal led to Minnesota and Wisconsin agreeing to a reimbursement provision under which Wisconsin would pay Minnesota for its losses. Payments began in 1975, with a one-year lag to gather information on final revenue collection. The states turned to the University of Michigan's Institute of Social Research (ISR) to create a methodology to calculate future payments. The ISR's methodology was later updated using income tax returns from 1995, and this revision served as the basis of payments from 1998 onward.

By 2002, Minnesota governor Jesse Ventura was concerned that the agreement was inadequately compensating his state and proposed eliminating it altogether. Minnesota's policymakers further argued that the ISR methodology did not adequately account for the cross-border flow of workers, being heavily in Wisconsin's favor. Finally, Minnesota claimed it was suffering additional revenue loss due to an average 17-month lag in reciprocity payments from Wisconsin. The agreement was salvaged when Wisconsin agreed to pay interest on the slow payments.

In 2009, then Minnesota Governor Tim Pawlenty proposed an agreement with Wisconsin to accelerate the payments from Wisconsin, which at that point amounted to nearly $100 million. When that failed, he authorized the revenue commissioner to terminate the reciprocity agreement, effective in September 2009. Termination forced Wisconsin to pay Minnesota all the money that had been delayed, resulting in revenue losses for Wisconsin in 2010 and 2011.

With the end of reciprocity, both Wisconsin and Minnesota allowed residents to have a credit against taxes paid in the other state (based on home sourcing rules), although Minnesota's credit was not as generous as Wisconsin's. In 2015, the U.S. Supreme Court ruled in Comptroller of the

[3]A lot of the discussion is taken from reports prepared by the Wisconsin Legislative Fiscal Bureau (Wisconsin Legislative Fiscal Bureau 2009, Wisconsin Legislative Fiscal Bureau 2011, Wisconsin Legislative Fiscal Bureau 2015), and the Minnesota House of Representatives (Minnesota House of Representatives 2002, Minnesota House of Representatives 2009) and the Minnesota Department of Revenue (Minnesota Commissioner of Revenue 2002, Minnesota Department of Revenue 2013).

Treasury of Maryland v. Wynne that if states tax all resident income (not just in-state income) they must allow a credit for taxes paid to other states.[4] Minnesota adjusted its credit to be in line with Wisconsin's starting in 2017, citing Wynne as rationale (Williams et al. 2021). Wisconsin had been holding out hope that the reciprocity agreement could be reinstated (Wisconsin had never repealed the statutes authorizing the agreement), but in announcing the adjusted credit in 2017, Minnesota Department of Revenue Commissioner Cynthia Bauerly stated there would be no return to reciprocity since the state would be forced to collect over $105 million annually from Wisconsin with risk of not being paid in a timely manner. This announcement effectively killed the chance of reciprocity being reinstated (CBS News Minnesota 2017).

Without administrative data, it is difficult to precisely assess the net fiscal impact from repealing reciprocity. When reciprocity was in place, Wisconsin's annual payments offset the fact that income from Wisconsin residents working in Minnesota is excluded from Minnesota's tax base. When the agreement was repealed, that income became part of Minnesota's tax base. However, Wisconsin no longer has to make annual payments. Differences in state tax bases and earnings profiles of the interstate commuters could tip the balance in one direction, but it seems likely that the net effect would be close to neutral for both states. To put the payments into perspective, $105 million is equal to 0.26% of fiscal year 2009 state and local revenue in Minnesota and 0.24% in Wisconsin.

Historically, both Wisconsin and Minnesota have had progressive income tax systems. In the years surrounding 2010, Wisconsin had 5 brackets and Minnesota 3. In 2012, Minnesota added a higher fourth bracket impacting folks filing jointly making over $261,510, whereas Wisconsin began a series of consolidations and tax rate reductions in 2013 that lead to their current 4 bracket structure. Wisconsin's rates have consistently been lower than corresponding Minnesota rates. Currently, Wisconsinites making under $34,000 are taxed at 3.54%, whereas in Minnesota they would be looking at 5.35%. The next bracket in Wisconsin is at 5.3% and extends to $374,000, whereas in Minnesota the tax rate is 6.80% and only extends to $163,000, where by it raises to 7.85% up to $284,810 before reaching its maximum rate of 9.85%, higher than Wisconsin's maximum of 7.6%.

While Minnesota's statutory rates are higher across the board than Wisconsin, rates do not

[4]Prior to Wynne, Maryland residents were granted a credit toward Maryland's state income taxes for income taxes paid in other states, but the credit did not extend to local (Maryland) income taxes. The Supreme Court ruled that this violated the Commerce Clause.

reveal the entire story. For example, Minnesota allows for a slightly higher standard deduction, whereas Wisconsin's standard deduction is income-dependent and starts decreasing at relatively low levels. Similarly, Minnesota and Wisconsin have different adjustments to federal taxable income that impact the amount of income that is actually taxed. For instance, Wisconsin has more income tax credits than Minnesota. To gain a better sense of how tax rates have differed between Wisconsin and Minnesota over time for an identical household, we leverage the NBER's TAXSIM model. Estimated effective average tax rates for four income levels are shown in Figure 1.

[Figure 1 here]

For an identical household (married, filing jointly with two dependents), average tax rates have been higher in Wisconsin for income levels of \$100,000 or less, and higher in Minnesota for income levels of \$250,000 or more. The most notable difference is for income levels of \$10,000 or less, where Minnesota's more generous standard deduction results in a large net subsidy for Minnesota residents relative to Wisconsin. At an income level of \$250,000, the difference between effective average tax rates is roughly 0.5% over the sample period, with Wisconsin consistently being the low tax state. There were also no noticeable changes in either state's effective rates at the time when reciprocity was repealed.

Repealing reciprocity increased compliance costs for all taxpayers and was, at best, liability neutral from a taxpayer's perspective. However, because of differences in effective marginal tax rates, different income tax bases, and differences in the generosity of their credits, it is possible that a large swath of interstate commuters in both states experience at least some increase in their overall tax liability post-dissolution. The increase in compliance costs may be also non-trivial, as both states require taxpayers who work in the neighboring state to make estimated quarterly tax payments for income taxes owed in their home state.

Finally, some Wisconsin interstate commuters were subjected to double withholding on their earnings, at least for a brief period of time following dissolution. Wisconsin law requires establishments with a nexus (or physical location) in the state to withhold taxes. Hence, if a Wisconsin interstate commuter happened to work for a firm with establishments in both states, then this taxpayer would have *both* Minnesota and Wisconsin income taxes withheld from their paycheck

(Wisconsin Department of Revenue 2010). Wisconsin would refund their withholding for taxes paid in Minnesota, but not until the end of the tax year. Given the burden this created for some Wisconsin residents, the state's Secretary of Revenue authorized a special withholding exemption three weeks after the dissolution became binding.[5] This experience, or a concern that the special exemption could be revoked in the future, might also have induced some Wisconsin residents to seek employment in their state of residence to avoid such complications.

3 Data and Identification Strategy

3.1 Commuting Data and Commuting Flows

Interstate commuting data are available from two Census Bureau sources: the American Community Survey (ACS), and the Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES). Both samples are a repeated cross-section. The ACS is based on a survey of households, and data are available at the county level using a 1/3/5 year sample starting in 2005/2007/2009. The ACS includes information on average commute times and whether an individual works remotely or commutes physically. A limitation is that an employee's workplace location is pegged as the location where they worked in the week prior to the survey period, whether that was their usual location or not (Graham et al. 2014).

LODES data, in contrast, identify work location based on the physical address of the employer as reported on the Quarterly Census of Employment and Wages reports. The jobholder's residential location comes from federal administrative records (Graham et al. 2014). Available starting in 2002, LODES provide annual counts of home-work locations down to the census block level. LODES data are derived from the larger Quarterly Workforce Indicators program, so they provide counts of wage and salary private-sector and government jobs covered by unemployment insurance, approximately 95% of all jobs. Unfortunately, LODES data do not allow tracking of the same individuals over time.

We measure commuting using the LODES data for several reasons. First, the granular geographic detail of home/work locations allows one to control for sub-county time-invariant factors, such as interstate access, that may be important in explaining commuting patterns. Second, unlike the ACS, LODES also reports home-work locations for three age categories and three categories

[5] The special withholding exemption was announced on January 20, 2010.

of monthly earnings, allowing us to explore the potential for heterogeneous effects among different strata of interstate commuters. Finally, LODES data are available for a longer period of time, so they provide a longer pre-treatment snapshot of commuting behavior.[6]

Between 2002 and 2009, an average of more than 70,000 people crossed the Minnesota-Wisconsin border for work annually. This flow was heavily skewed in favor of Minnesota, as 3 Wisconsinites commuted to Minnesota for every 1 Minnesotan who commuted to Wisconsin. Interstate commuters from both states are largely clustered near one of the three shared metro areas: Minneapolis–St. Paul–Bloomington, Duluth-Superior, and La Crosse-Onalaska. Half of all interstate commuters live in, or border, the Minneapolis–St. Paul MSA, which is among the top 20 largest metro areas in the nation and has a population of 3.7 million.

The spatial distribution of residence and workplace destinations for interstate commuters from both states is depicted in Figure 2. The official border for each of the multi-state MSAs is delineated by a thick black line. Panel A shows the county-level intensity of the top counties where Minnesotans who commute to Wisconsin both live and work. Of these roughly 18,000 commuters, sixty percent live in five counties: Houston and Winona Counties in the La Crosse region, St. Louis and Carlton Counties in the Duluth region, and Washington County in the Minneapolis-St. Paul region. In terms of work destinations, 50% of these Minnesotans work in two counties in Wisconsin: La Crosse (approximately 4800 people) and Douglas (approximately 3600 people).

[Figure 2 here]

Wisconsinites commuting to Minnesota are also tightly clustered, as shown in Panel B. Five counties in Wisconsin that border Minnesota - Pierce, Polk, and St. Croix in the Minneapolis-St. Paul region, Douglas in the Duluth region, and La Crosse in the La Crosse region - are home to 75% of the state's 58,000 interstate commuters. One-third of these commuters alone live in St. Croix County, which is part of the Minneapolis–St. Paul MSA.

The flow of Wisconsinites to the urban core(s) of Minneapolis-St. Paul and Duluth far outnumber the flow of Minnesotans in these regions who work in Wisconsin. The La Crosse metro region

[6] One drawback of the LODES data is that one does not know for certain whether a worker physically commutes. A comparison of the proximity between home/work locations suggests most commuting is physical. Additionally, 1-year ACS surveys indicate fewer than 2% of respondents reported working remotely between 2005 and 2018.

is the only shared metro region where interstate commuters from Minnesota outnumber those from Wisconsin. In all three regions, the net flow of interstate commuters is heavily tilted in favor of the counties that are home to the area's largest cities.

3.2 Treatment and Comparison Groups

Using the clustering of residence and workplace locations illustrated in Figure 2 as a guide, treatment groups for Minnesota and Wisconsin's interstate commuters are formed to capture the primary commuting patterns in each state. For Wisconsin, treated counties include Pierce, Polk, St. Croix, Douglas, and La Crosse Counties. In Minnesota, the treated counties are Carlton, Houston, St. Louis, Washington, and Winona Counties. Interstate commuters from these 10 counties account for 75% of the total interstate commuting flow.

Because only individuals who cross the border were affected by the dissolution of reciprocity, one path to identify a causal effect is to compare the commuting behavior of individuals crossing the border to that of individuals living and working in the same state who were unaffected by the policy change. However, it is well established that there are differences between skill levels, productivity, and wages of workers in metro versus non-metro areas, as well as in different sized cities (Roca and Puga 2016; Glaeser and Mare 2001). Because we are unable to observe these important characteristics, we rely on several comparison groups of commuters – both interstate and intrastate – as robustness checks to minimize the risk of unobservables.

As a baseline, we compare interstate commuters from Wisconsin and Minnesota with unaffected workers who live and work in the same state and commute across county lines to work in the same destination counties. Residents of the same regions may have similar cultural norms about work and share preferences for regional amenities. Since these individuals also work in the same destination counties, this may reduce the threat from local unobservables such as public transit accessibility. Figure 3 illustrates the treatment and *same region* comparison group for Wisconsin's interstate commuters.

[Figure 3 here]

Given sub-county heterogeneity, we tabulate the number of commuters in each census tract in the treatment and comparison group counties who work in the same destination county (or counties). Consider the Duluth MSA, which officially consists of three counties in Minnesota and one in Wisconsin. Nearly all Wisconsinites who commute from Douglas County work in St. Louis County, MN, home to the region's principal city of Duluth.

The Wisconsin treatment group consists of the number of interstate commuters from each of Douglas County's 13 census tracts (shaded in green in Figure 3) who work anywhere in St. Louis County, Minnesota (shaded in orange). The comparison group consists of the 32 census tracts from two Minnesota counties within the official MSA boundary (Carlton and Lake) and two counties that are contiguous to St. Louis County but outside the official MSA boundary (Koochiching and Itasca). For each census tract in these counties, we tabulate the number of (intrastate) commuters who live in Minnesota and cross county lines and to work in St. Louis County. Comparison group counties are shaded in purple in Figure 3.

The Minneapolis-St. Paul MSA is roughly 12 times larger in population than the Duluth MSA, and 26 times larger than the La Crosse MSA. Because of the region's size, there are job centers in multiple counties in Minnesota. We therefore adjust the construction of the treated and comparison units and tabulate the number of commuters to each of the job centers in the region. Pre-dissolution, more than 92% of Wisconsinites who commuted to the Minnesota side of the region worked in either Dakota County, Hennepin County (home to Minneapolis), Ramsey County (home to St. Paul), or Washington County. These four job destination counties are shaded in orange in Figure 3.

For each of the 32 treated (Wisconsin) census tracts in this region, we (separately) calculate the number of individuals who commute to each of the four primary work counties. The comparison group consists of 173 census tracts from the nine Minnesota counties in the metro area that are not a primary work destination. Since the number of commuters is tabulated for each work county destination, the Minneapolis-St. Paul region yields 820 home tract-work destination observations annually (32 x 4 treated and 173 x 4 comparison).

Across all three multi-state metro regions, there are a total of 70 treated census tracts for Wisconsin's interstate commuters who live in Pierce, Polk, St. Croix, Douglas, and La Crosse Counties. This *same region* comparison group consists of 230 census tracts from the purple counties shown in Figure 3.

We follow the same process to form the *same region* comparison group for Minnesota's interstate commuters. Across the multi-state regions, there are a total of 139 treated census tracts for

Minnesota's interstate commuters who live in Carlton, Houston, St. Louis, Winona, and Washington Counties. Their (same region) comparison group consists of workers from 113 census tracts who live in a Wisconsin county that borders the same Wisconsin counties where Minnesotans work. The counties (and census tract counts) that are used to form the two treatment groups and every comparison group are documented in detail in Data Appendix A.

While the same region comparison groups control for unobserved shocks at the place of employment, this comparison group is vulnerable to individuals who move across the border because of reciprocity. For instance, suppose a St. Croix County, WI resident keeps their same job (in say Hennepin County, MN) and moves to Minnesota post-reciprocity. If they move to Hennepin County, MN, then this is not a problem because the comparison group excludes individuals who live and work in the same county. However, if they move to Scott County, MN and commute to Hennepin County, then this individual would part of the treatment group in the pre-treatment period and part of the comparison group in the post-treatment period.

Due to the risk from interstate movers, which we address in greater detail in Section 4.2, we focus on the number of commuters rather than the commuting rate because of the scenario outlined in the preceding paragraph. Moreover, as a robustness check to the baseline comparison groups, we also form several additional comparison groups, each having advantages and disadvantages. For instance, in addition to movers, the *same region* comparison groups do not control for state-specific factors that could affect commuters in only one state. Examples could include rideshare programs or other similar statewide or regional incentives that could raise or lower commuting costs for residents of only one state.

To mitigate concerns over state-specific factors, we compare Wisconsin and Minnesota interstate commuters with intrastate commuters from *internal* metro regions in both states. These commuters should be insulated from the policies of neighboring states, but they would be impacted by state policies affecting residents of only one state. In short, an *internal intrastate* Wisconsin comparison group will better control for Wisconsin-specific unobservables, while an *internal intrastate* Minnesota comparison group will better control for Minnesota-specific unobservables. Since these internal comparison commuters also live and work in the upper Midwest, they may share similar cultural norms and regional levels of diversity that affect economic outcomes (Ottaviano and Peri 2005).

For the *internal intrastate* Wisconsin and Minnesota comparison groups (documented in Data Appendix A), we tabulate the number of workers who cross county lines to commute to large work destination counties. As one example, the Oshkosh metro region in Wisconsin is located in the interior of the state (far away from other state borders), and Winnebago County is the employment hub of the region. The comparison group from the Oshkosh region is the number of residents in every census tract of Calumet, Fond du Lac, Green Lake, Outagamie, Waupaca, and Waushara County who commute to (bordering) Winnebago County for work. To ensure we are capturing broad internal intrastate commuting trends in each state, Wisconsin's internal intrastate comparison group includes commuters from the Oshkosh region, Wausau region, and Madison region, while Minnesota's internal intrastate comparison group encompasses the St. Cloud, Beltrami, and Mankato regions.

The internal intrastate comparison groups are not without limitations. These regions are much smaller (in terms of population) than the Minneapolis-St. Paul region and only capture commuters who live and work in the same state. Considering that movers to multi-state metro regions are more likely to reside in the low tax state (Coomes and Hoyt 2008) and that larger regions may lead to greater skill acquisition that is independent of initial ability (Roca and Puga 2016), comparing interstate commuters from Minnesota and Wisconsin to other populated metro areas may be a more suitable counterfactual.

We form five additional comparison groups from populated metro regions. The regions include Denver, CO, St. Louis, MO-IL, Chicago, IL-WI-IN, Philadelphia, PA-NJ, and Cincinnati, OH-IN-KY. Denver is the most populated *internal* metro region in the central U.S. that has an urban core similar in size to the Minneapolis-St. Paul region. We also focus on the St. Louis region because this is the most populated multi-state metro region in the central U.S. where interstate commuters (from Illinois and Missouri) do not have the benefit of personal income tax reciprocity. The final three comparison groups – Chicago, Philadelphia, and Cincinnati – are the three most populated multi-state metro areas where interstate commuters have benefited from stable income tax reciprocity agreements for many years.

For the Denver region, the comparison group consists of the number of commuters from each census tract in counties that border the urban core, Denver County. Comparison groups for the remaining multi-state regions are formed differently because commuting is heavily tilted in favor of the central city. As an example, in Philadelphia, we tabulate the number of commuters in each census tract in four New Jersey border counties within the MSA who work in Philadelphia County to capture the NJ-to-PA flow. To capture the minority flows from PA-to-NJ, we tabulate the number of commuters in each census tract in four Pennsylvania border counties in the MSA who work *anywhere* in New Jersey.[7]

[Table 1 here]

Descriptive statistics of commuters for the treatment and comparison regions are presented in Table 1. Over the entire sample period, an average of 185.2 Wisconsin residents (per census tract) in the treated counties crossed the border to work in Minnesota. This is almost three times larger than the 69.2 average number of commuters (per census tract) who live in Minnesota and work in Wisconsin.

Although this is not discernible from Table 1, the distribution of the number of commuters is skewed to the right in both treatment groups and in every comparison group. Some census tracts in every region have many commuters, because of interstate access, proximity to job centers, or other accessibility features such as a bridge, while some tracts have very few commuters.

The age distribution of interstate commuters is reasonably comparable between Wisconsin and Minnesota. Twenty-one percent of interstate commuters who live in Wisconsin are ages 29 and under, 63% are between 30 and 54 years old, and 16% are 55 or older. In Minnesota, these percentages are 22%, 58%, and 20%, respectively.

In terms of earnings, Wisconsin has a larger fraction of high-earnings commuters and a smaller fraction of low- and mid-earnings commuters than Minnesota. Sixteen percent of Wisconsin's interstate commuters are low-earners ($1,250 per month or less), 28% are mid-earners (between $1,250 and $3,333), and 56% are high-earners ($3,333 or more). Forty-four percent of Minnesota residents who work in Wisconsin are high-earners, 34% are mid-earners, and 22% are low-earners.

[7] If one were to tabulate the number of commuters from each census tract in a Pennsylvania county to a specific county in New Jersey, there would be a substantial number of zero values because most interstate commuters in the region live in New Jersey. For this reason, the multi-state metro region comparison groups tabulate interstate commuters from the state with the central city (Pennsylvania, Illinois, and Ohio) to any location in the bordering state. Data Appendix A documents the formation of each comparison group.

3.3 Empirical Specification

Minnesota announced in September 2009 that the reciprocity agreement would end on January 1, 2010. Since the LODES data uses the second quarter of the year as the reference period, our empirical strategy (separately) estimates the change in the number of interstate commuters from Wisconsin and Minnesota relative to each comparison group outlined in the previous section using 2010 as the treatment date.

A regression-based difference-in-differences approach is perhaps the simplest way to estimate the average treatment effect on the treated (ATT) census tracts. The "parallel trends" assumption must hold for a difference-in-differences estimate to recover an unbiased estimate of the ATT. In our setting, this means that the post-treatment number of commuters from the (untreated) comparison group census tracts are a valid counterfactual for the unobserved potential outcome for the treated census tracts.

Although the parallel trends assumption is untestable because it is based on potential outcomes that are not observed, it is standard to compare the pre-treatment outcomes in the treated and comparison groups. If there is no evidence of a significant difference before treatment, then one may be more confident that the parallel trends assumption would be valid post-treatment.

We uncovered significant pre-trends violations between interstate commuters from Wisconsin and Minnesota when compared to many of the comparison groups using a regression-based approach.[8] To obtain more credible estimates of the average treatment effect on the treated (ATT) census tracts for Minnesota and Wisconsin's interstate commuters, we instead utilize the partially pooled synthetic control method recently developed by Ben-Michael et al. (2022).

As a point of departure, consider a canonical synthetic control method (SCM) where the unobserved potential outcome for a single treated unit j – how the number of commuters from a census tract would have evolved if reciprocity remained in place – is estimated from a weighted-average of untreated units. With a potential donor pool of 1, 2, ..., N units, Ben-Michael et al. (2022)

[8] The regression models included year fixed effects and (home X work destination) fixed effects. The pre-trends violations persisted when we included time-varying covariates, unit-specific linear trends, measured commuting as the number of commuters or commuting rate, or used a doubly-robust difference-in-differences approach (see Callaway and Sant'Anna 2021).

consider a synthetic control method of the form:

$$\min_{\gamma_j \in \Delta_j^{scm}} \frac{1}{L_j} \sum_{l=1}^{L_j} \left(Y_{jTj-l} - \sum_{i=1}^{N} \gamma_{ij} Y_{jTj-l} \right)^2 + \lambda \sum_{i=1}^{N} \gamma_{ij}^2, \tag{1}$$

where Y is the outcome of interest, L_j is the number of pre-treatment periods, T is the total number of time periods, and $\gamma_j \in \Delta_j^{scm}$ denote the SCM weights. The individual weights, γ_{ij}, are assumed to sum to unity and be non-negative.

This formulation differs from Abadie (2005) and Abadie et al. (2010) in two ways. First, following Doudchenko and Imbens (2016), the weights in equation (1) are selected by directly optimizing over the pre-treatment fit rather than selecting them from a nested optimization problem. Second, the optimization problem includes a regularization parameter, λ, which penalizes the sum of the squared weights. This reduces the risk of over-fitting the model to noise rather than signal (Ben-Michael et al. 2022), which can be a concern in SCM (Abadie et al. 2015).

With a set of weights that solves equation (1), the SCM estimate of the unobserved potential outcome for treated unit j in post-treatment period k is given by:

$$\hat{Y}_{jT_j+k} = \sum_{i=1}^{N} \hat{\gamma}_{ij} Y_{iT_j+k}, \tag{2}$$

where the estimated treatment effect for unit j at time k can be expressed as $\hat{\tau}_{jk} = Y_{jT_j+k} - \hat{Y}_{jT_j+k}$.

If one restricts the sample to only pre-treatment data ($k < 0$), then the difference between the observed outcome and synthetic counterfactual outcome is a placebo treatment effect. Using this reformulation and setting the regularization parameter to zero, the SCM objective can be expressed as minimizing the mean squared error of the placebo treatment effect on pre-treatment outcomes (Ben-Michael et al. 2022). [9] Mathematically, this is given by:

$$\left(q_j\left(\hat{\gamma}_j\right)\right)^2 = \frac{1}{L_j} \sum_{l=1}^{L_j} \left(Y_{jTj-l} - \sum_{i=1}^{N} \hat{\gamma}_{ij} Y_{jTj-l} \right)^2. \tag{3}$$

[9] Ben-Michael et al. (2022) have a companion paper, Ben-Michael et al. (2021), showing that λ becomes increasingly important in estimating the weights when the difference between the number of treated units and number of pre-treatment periods grows. In our application, different values of λ have no practical effect on the weights so we simply set $\lambda = 0$ in the SCM models. Appendix Table B.1 provides a table comparing our ATT estimates setting $\lambda = 0$ to the estimates when $\lambda = 10$, which is considered to be a large regularization parameter value.

If the synthetic counterfactual and observed outcome for treated unit j are equal in every pre-treatment period, then $q_j(\hat{\gamma}_j)$ equals zero.

Ben-Michael et al. (2022) extend this SCM framework for a single treated unit to a more general setting with panel data and (potentially) staggered treatment timing. They propose a "partially pooled SCM" estimator that minimizes the weighted-average of one approach that estimates a separate synthetic control for each treated unit and a second approach that estimates a single (or pooled) synthetic control for the average of the treated units. This weighted-average estimator is motivated by the fact that, when there are a total of J treated units ($J > 1$), Ben-Michael et al. (2022) show that if $\hat{\tau}_{jk}$ denotes the estimated treatement effect for unit j at time k, then the overall average treatment effect on the treated in period k can be expressed as:

$$\widehat{ATT}_k = \frac{1}{J}\sum_{j=1}^{J}\hat{\tau}_{jk} = \underbrace{\frac{1}{J}\sum_{j=1}^{J}\left[Y_{jT_j+k} - \sum_{i=1}^{N}\hat{\gamma}_{ij}Y_{iT_j+k}\right]}_{\text{average of individual SCMs}} = \underbrace{\frac{1}{J}\sum_{j=1}^{J}Y_{jT_j+k} - \sum_{i=1}^{N}\sum_{j=1}^{J}\frac{\hat{\gamma}_{ij}}{J}Y_{iT_j+k}}_{\text{one pooled SCM of the average}} \tag{4}$$

In other words, with multiple treated units, the $\widehat{ATT}_k$ can be expressed both as the average of the individual unit SCM estimates and as a single SCM for the (pooled) average treated unit. Under the assumption that the unobserved potential outcome for treated units is generated by either an autoregressive process or a linear factor model, the estimation error in $\widehat{ATT}_k$ may also be decomposed into a term that depends on the individual unit SCM fits, a term that depends on the pooled SCM fit, and random noise (Ben-Michael et al. 2022).

Using the equivalent relationship noted in equation (4), Ben-Michael et al. (2022) derive the root mean squared error of the pre-treatment fits for each expression of $\widehat{ATT}_k$. The "partially pooled SCM" minimizes the weighted average of the pooled and separate mean squared pre-treatment errors from comparing the observed (pre-treatment) outcomes with their SCM(s).

If α denotes a potential permanent additive (or intercept) difference between treated and control units and Γ notes the N x J matrix of SCM weights, $[\gamma_1, ..., \gamma_J]$, the partially pooled SCM is the matrix that minimizes:

$$\min_{\alpha\in\mathbb{R}^J,\Gamma\in\Delta^{scm}} \nu\,(\tilde{q}^{pool}(\alpha,\Gamma))^2 + (1-\nu)\,(\tilde{q}^{sep}(\alpha,\Gamma))^2 + \lambda\|\Gamma\|_F^2, \tag{5}$$

where $\tilde{q}^{pool}$ and $\tilde{q}^{sep}$ denote the (normalized) mean squared pre-treatment error from the pooled and separate SCM methods, respectively. [10] The sum of the squared weights are penalized by the Frobenius norm.

The parameter $\nu \in [0, 1]$ is selected by the researcher and controls the relative weighting between the separate and pooled SCM approaches. Setting $\nu = 0$ estimates a separate SCM for every treated unit and ignores the pooled fit, whereas $\nu = 1$ first averages across the treated units and estimates a single SCM (ignoring individual fits). Ben-Michael et al. (2022) propose a data-driven heuristic to select ν based on the goal of balancing individual SCM fits and the overall pooled (or average) SCM fit.

If one is interested in minimizing bias in the overall average ATT and the individual SCM estimates are of secondary interest, then Ben-Michael et al. (2022) recommend setting $\nu = 1$ so that the SCM weights are chosen to minimize the pre-treatment fit between the average (pre-treatment) treated unit and its synthetic counterfactual ($\nu = 1$ averages across all the treated units before performing SCM). This reduces the influence of individual treated units with extreme values or those with poor pre-treatment fits if the overall ATT were instead estimated from averaging *after* estimating individual SCMs (setting $\nu = 0$). Given our goal of obtaining a reliable estimate of the overall average treatment effect, we follow this recommendation and set $\nu = 1$. [11]

We also explored selecting weights by balancing on the number of interstate commuters and several time-varying (county-level) covariates, such as the ratio of median home prices to median household income, violent crime arrests per 10,000 residents, public school instructional spending per pupil, and the fraction of local public school revenue generated from local property taxes. These are observable characteristics that may be correlated with one's decision to live and work in different counties. Including these additional covariates never improved the pre-treatment over matching on just the number of commuters.[12] We therefore only report estimates where the weights

[10]See Ben-Michael et al. (2022) for a detailed derivation of the normalized mean squared pre-treatment error expressions, $\tilde{q}^{pool}$ and $\tilde{q}^{sep}$.

[11]We also estimated the average treatment effect on the treated units by allowing ν to lie between 0 and 1 based upon Ben-Michael et al. (2022)'s recommended data-driven heuristic. The heuristic selected 1 as the optimal value for ν in nearly every specification. As a robustness check, however, we re-estimated every specification forcing $\nu = 0$, which generates an individual SCM for each treated unit and then averages the individual estimates to estimate $\widehat{ATT}_k$. These estimated treatment effects were approximately 30% larger (in absolute value) than when $\nu = 1$. It is also important to note that the statistical significance of our findings did not change when we forced $\nu = 0$. Appendix Table B.2 compares the ATT estimates when $\nu = 0$ with our results in the paper.

[12]We balanced on time-varying covariates in the pre-treatment period in two ways. First, (county-level) covariates were measured at the home county where interstate commuters lived. We also measured the covariates as the

were selected by balancing on the (pre-treatment) number of interstate commuters.

4 Empirical Results

4.1 Baseline results

Baseline results of the impact of repealing reciprocity on the number of interstate commuters (per census tract) are presented in Figures 4 through 7. Due to the skewness of the distribution of commuter counts (noted in Section 3.2), the number of commuters was first transformed using the inverse hyperbolic sine prior to estimating the partially pooled synthetic control method.[13] This transformation approximates the natural logarithm while retaining zero-valued observations (Bellemare and Wichman 2020). The transformation also narrows the range of the data, leading to superior pre-treatment fits over the untransformed data.

[Figure 4 here]

Figure 4 plots the event study treatment effect estimates for Wisconsin's interstate commuters compared to the *same region* comparison group (Panel A), the *internal* Wisconsin comparison group (Panel B), the *internal* Minnesota comparison group (Panel C), and the Denver, CO comparison group (Panel D).[14] Ninety-five percent confidence intervals, formed via the wild bootstrap, are also shown for each point estimate.[15] Finally, each panel reports the overall average ATT across all post-treatment periods and the sum of the squared pre-treatment errors as a measure-of-fit.

Across all four panels, the *largest* pre-treatment sum of squared errors between the actual number of commuters and the synthetic counterfactual is 4.9e-15 (Panel B), indicating a very precise pre-treatment fit regardless of the comparison group. More importantly, we witness a notable, permanent drop in the number of WI commuters across all comparison groups. This drop represents a 2 to 3 percentage decrease in WI commuters relative to the comparison groups, except

difference between the home county and work county to capture origin and destination effects. Neither approach improved the pre-treatment SCM fit over balancing solely on the number of commuters.

[13] The inverse hyperbolic sine of x is given by: $\text{IHS}(x) = log(x + \sqrt{x^2 + 1})$

[14] The exact composition of each comparison group is documented in Data Appendix A.

[15] The wild bootstrap procedure proposed by Ben-Michael et al. (2022) extends the bootstrap procedure for matching estimators proposed by Otsu and Rai (2017). Rather than re-sampling units, the procedure perturbs the outcome (i.e., number of commuters) in the treated and comparison census tracts with random values. The synthetic control weights remain fixed in each iteration so that the bootstrapped distribution is based on uncertainty in the number of commuters. See Ben-Michael et al. (2022) for additional details.

for Denver, where the decline is strongest at just over 7 percent. [16]

[Figure 5 here]

Because the Minneapolis MSA crosses two states, we next expand the comparison to the synthetic counterfactuals we created for the multi-state metro regions of Chicago (Panel A), Cincinnati (Panel B), Philadelphia (Panel C) and St. Louis (Panel D). St. Louis is the only multistate MSA in our grouping lacking an income reciprocity agreement, which gives us another angle of comparison to explore.

The corresponding event study plots are provided in Figure 5, and once again we see a similar permanent reduction in Wisconsin's interstate commuters, with the decline representing between a 1.7 and 3.9 percent reduction depending on the comparison region. Note that these estimates on our par with the estimates from Figure 4, which provides further comfort that the decline we witness is not due to a particular specification of comparison. Moreover, the fact that the St. Louis comparison falls right in the middle with a 2.6% decline suggests the presence of an income tax reciprocity agreement, while helpful, is not crucial in creating the comparison group.

We repeat these exercises for Minnesota commuters in Figures 6 and 7. As was the case with Wisconsin, our pre-treatment fit is excellent. In contrast to Wisconsin, however, we do not find consistent evidence that repealing reciprocity affected the interstate commuting behavior of Minnesota residents. Six of our 8 comparison groups show no change whatsoever, whereas the Philadelphia and internal Wisconsin regions suggest a slight increase. Thus, the takeaway from Figures 4-7 is that the repeal had differential impacts on the two states, with a strong negative impact on Wisconsin commuters.

[Figures 6 and 7 here]

As a robustness check to the baseline estimates, we also perform in-time placebo tests using 2007 as the placebo treatment date. These results, presented in Appendix C, do not show any evidence of

[16] The mean and median inverse hyperbolic sine of Wisconsin's (treated) number of commuters is 5.22 and 5.27, respectively. Given an overall ATT estimate of -0.141 for the *same region* comparison group (Panel A in Figure 4), this suggests that the number of interstate commuters from Wisconsin fell 2.7% after reciprocity was repealed. Percentage reductions for other comparison groups follow accordingly.

sustained differences between commuting behavior in the treatment groups and comparison groups in the years just preceding the repeal of reciprocity.

4.2 Reciprocity and interstate movers

As noted in Section 3.2, repealing reciprocity could induce interstate commuters to seek employment in their state of residence or, potentially, to even move across state lines. In this section, we explore whether reciprocity affected interstate movers using the Internal Revenue Service's (IRS) Statistics of Income population migration data. Data for each year covers between 95 and 98% of total annual (federal) tax return filings.

The IRS uses year-to-year address changes reported on individual income tax returns to shed light on migration patterns down to a county level. The data report the number of tax returns and the number of personal exemptions filed. According to the IRS, the number of tax returns approximates the number of households, while the number of personal exemptions approximates the number of individuals. Since these data are based on federal personal income tax filings, an individual (or household) would be not be captured if their adjusted gross income fell below the threshold required to submit a federal tax return. A second limitation of these data is that they cannot be linked with other data, so we do not know the location where these taxpayers are employed.

If reciprocity may induce individuals/households to move across state lines, any effect may be strongest in areas with the tightest interstate commuting linkages. We therefore focus on the same 5 Minnesota counties and 5 Wisconsin counties that we used to form the commuting treatment groups.[17]

Given that we know the new home county for interstate movers, we construct four different outcome variables to assess the causal effect of repealing reciprocity. For each of the 10 treated counties, we tabluate: (1) the number of individuals (personal exemptions) who moved from county i to a border county in state j in year t; (2) the number of individuals (personal exemptions) who moved from county i to any county in state j in year t; (3) the number of households (tax returns) who moved from county i to a border county in state j in year t; (4) the number of households (tax

[17] As a robustness check, we also estimated the average treatment effect of repealing reciprocity on movers by redefining treated counties to be: (a) every border county in Wisconsin and Minnesota (a total of 23 counties), and (b) every border county in Wisconsin and Minnesota plus every county adjacent to those border counties (39 counties). We find no evidence of a significant change in the number of interstate moves after reciprocity was repealed using these alternative treatment group definitions. These additional results are available upon request.

returns) who moved from county i to *any* county in state j in year t. On average, between 2002 and 2009, approximately 2,200 Minnesota individuals (exemptions) in the treated counties relocated to a Wisconsin border county annually. This is roughly 40% larger than the 1,600 Wisconsin individuals (exemptions) residing in a treated county who moved across state lines in a typical year to relocate to a Minnesota border county.

For the comparison group, we leverage the long-term stability of personal income tax reciprocity agreements in other contiguous state pairs. There are a total of 25 other contiguous state pairs where income tax reciprocity remained unchanged over our sample period (2002 to 2019).[18] This will give a sense of how interstate movers between Minnesota and Wisconsin compared with interstate movers from other states where tax reciprocity remained intact. There are a total of 322 contiguous border pairs within the 25 state pairs.

We estimate the average treatment effect on movers using the same partially pooled SCM approach applied to the number of commuters (setting $\nu = 1$). To collapse the range of the data and mitigate issues from skewness, the number of movers is transformed using the inverse hyperbolic sine prior to estimation. The results of these estimates are shown in Figure 8.[19]

[Figure 8 here]

Panels A and B in Figure 8 show the SCM estimates when movers are approximated by the number of households (filings). Panel A shows results when movers are tabulated to a border county in the neighboring state, while Panel B shows results when movers are tabulated to any county in the neighboring state. Panels C and D approximate movers using the number of individuals (exemptions). Panel C reports moves to a border county, while Panel D reports moves to any county in the state.

Across all four measures of movers, the results show no evidence of a significant change between Wisconsin and Minnesota post-reciprocity relative to the synthetic counterfactual. Although we see point estimates grow in a positive manner post 2016 for all comparison groups, the error bands

[18] See Rork and Wagner (2012) for complete details on states with income tax reciprocity agreements. Using postal abbreviation codes, the 25 other contiguous state pairs with tax reciprocity that constitute the comparison group include: IL-MA, IL-IA, IL-WI, IN-MI, IN-KY, IN-OH, IN-WI, KY-VA, KY-WV, KY-OH, MD-WV, MD-PA, MD-VA, MT-ND, MN-ND, MN-MI, MI-WI, MI-OH, NJ-PA, OH-WV, OH-PA, PA-WV, PA-VA, PA-NJ, VA-WV.

[19] The pre-treatment fit is better when the number of movers is transformed by the inverse hyperbolic sine. Our findings do not change if we instead estimate the SCM models using the untransformed number of movers.

grow even faster, leading us to this null conclusion.

When we combine this lack of mobility with our prior evidence that fewer Wisconsinites crossed the border to work post-reciprocity, we are left to conclude that those individuals either dropped out of the labor force, became self-employed, or found alternative employment within Wisconsin.

Since the commuting data are repeated cross-sections (LODES or ACS), it is not possible to know with certainty how Wisconsin's interstate commuters reacted to repealing reciprocity. An individual who transitions to self-employment would not be captured in the LODES data because they are based on establishment payroll counts. In addition, the estimated response is modest when compared to the overall number of jobs. For instance, St.Croix County, Wisconsin is home to the largest number of interstate commuters (approximately 18,000). Our estimates indicate a 3% reduction in the number of commuters, which equates to roughly 540 people. If all of these individuals transitioned to payroll employment in their county of residence, this would equal less than one percent of the total jobs in St.Croix. Since some of these Wisconsin residents could also work in (Wisconsin) counties that differ from their county of residence, it would be difficult to detect a meaningful spatial reorganization of jobs from Minnesota to Wisconsin.

4.3 Commuters by earnings and age

While we are able to rule out migration as an explanation, there is a concern that aggregating all commuters together could cause us to miss impacts to commuters of certain ages or income levels. Fortunately, the LODES data are stratified by the Census Bureau into 3 age brackets and 3 earnings brackets. To keep the empirical results manageable, we report estimates comparing treated commuters in Wisconsin and Minnesota to a synthetic counterfactual formed from their respective *same region* comparison groups for several reasons. First, these comparison groups have more similar distributions of age/earnings commuters with the treatment group than other regions. Second, as noted previously, these comparison groups control for unobserved shocks at the county of employment. Finally, the estimated treatment effects from the *same region* comparison group for Minnesota and Wisconsin's commuters, presented in Section 4.1, were approximately at the midpoint among all the comparison groups.

[Table 2 here]

Table 2 presents the overall average ATT for interstate commuters, stratifying by age and income. Figures corresponding to each estimate reported in Appendix Figures B.1 - B.4. When we stratify by age, we find negative impacts on Wisconsin commuting for all age brackets, although only the 55 and older group is statistically insignificant. Our estimated decline in commuters is over 3% for the other two groups. This is at the high end of our estimates from Figures 4 and 5, and it is consistent with our aggregated estimates that include a large group of commuters that are not exhibiting an impact.

Similarly, when stratifying by income we find a decline in Wisconsin commuters across all income groups, and again the estimates are consistent with what we found previously. When we combine this with the lack of any impact by age or income of our Minnesota commuters (Appendix Figures B.3 and B.4), we take comfort that aggregating all our commuters together is not obscuring an impact to a subgroup of those commuters.

5 Conclusion

This paper utilized the dissolution of the income tax reciprocity agreement between Minnesota and Wisconsin to explore how changes in personal income taxation impact interstate commuting patterns. We find that the number of Wisconsin residents commuting to Minnesota employers drops by an average of 3 to 5% in bordering counties. In addition, we find that the impact is strongest for those in the middle of the earnings distribution, which today corresponds to the largest difference in marginal tax rates between the two states.

Our results were potentially dampened by the fact that some residents may reasonably have expected the agreement to be reinstated. Wisconsin consistently lobbied for its renewal as late as 2017, which is when Minnesota put the issue to rest by allowing taxes paid in Wisconsin to be fully credited back against Minnesota taxes.

In a Mills-Muth model, the spatial equilibrium that forms is dependent on the tradeoff commuters are willing to make with their after tax-income between commuting costs and housing prices. For all cross-border commuters, the dissolution of the reciprocity agreement increased the costs of tax compliance, adding an additional cost to the commuting calculation. The most price sensitive commuters/residents to these commuting changes, all else equal, would be located on the outskirts of the urban core.

Given that the largest urban cores of the MSAs are located on the Minnesota side of the border, the most price sensitive commuters would be located either in inner Minnesota (further away from the border and urban cores) or across the border into Wisconsin. These inner Minnesotans were unlikely to be the ones commuting to Wisconsin given the distance, which is consistent with our finding of no effect for the Minnesotans. For the Wisconsinites commuting to Minnesota, they could offset some commuting costs by moving closer, but given that we find a drop in commuting from all border counties and no evidence of increased migration effects into Minnesota, this seems unlikely. The only other option for Wisconsinites would be to shift their employment within Wisconsin. The fact we find a stronger effect for those under the age of 55 is suggestive of such an impact.

While our results show a sensitivity to changes in income taxes and physical commuting, the post-Covid rise of telecommuting adds a new wrinkle to the calculus. The loss of physical commuting would allow employees to spread out farther in a Mills-Muth model, which in turn means more individuals may find themselves in situations where they are employed by a firm not located in their state of residence. Differences in state tax systems may become more salient to residents as a result, thereby opening a new front in the tax competition wars between states. Given the small magnitude of our results suggests the revenue gains from competition would be modest at best, states could consider pivoting into implementing additional convenience rules as an alternative.

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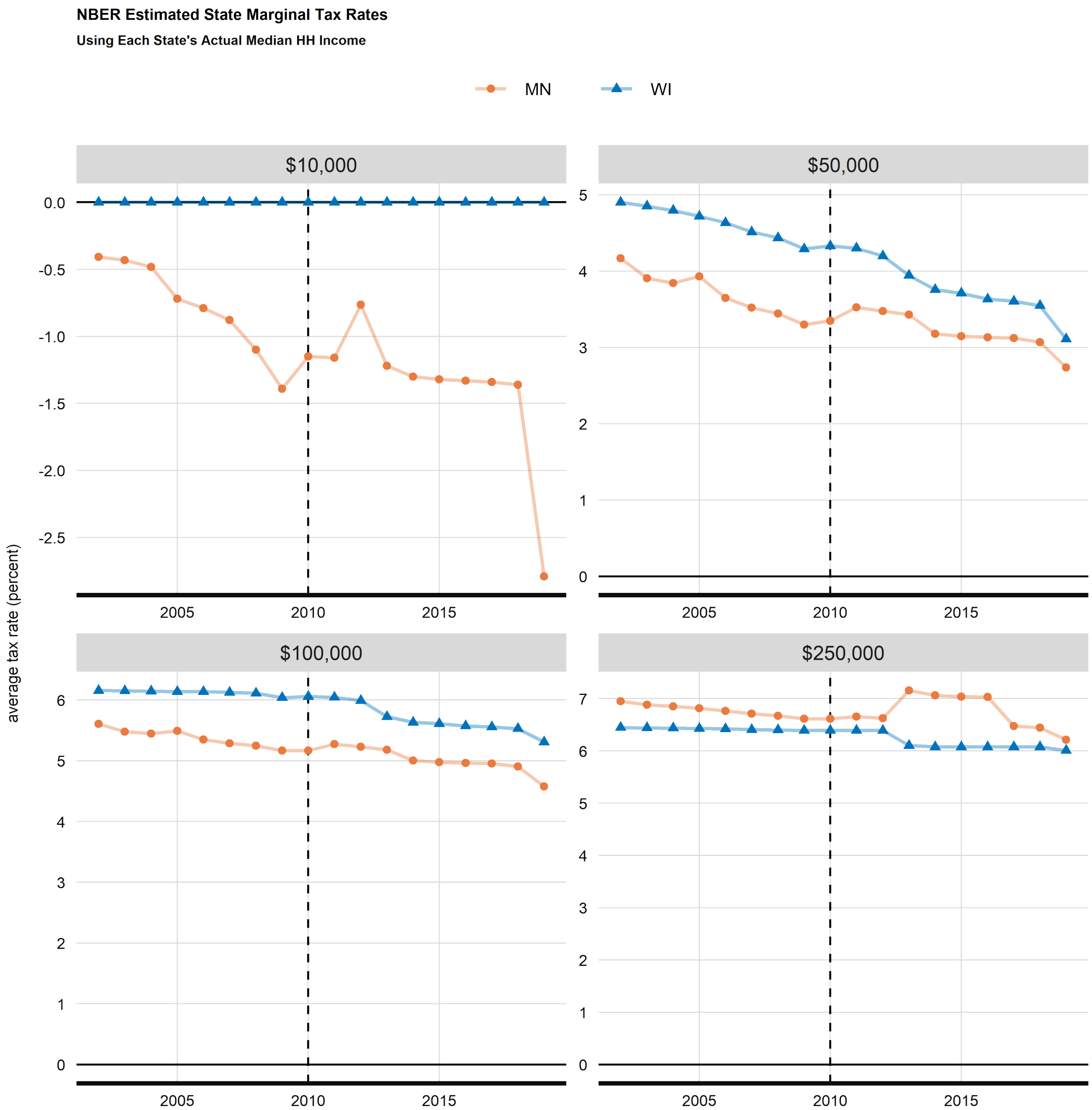
Figure 1: Estimated State Average Tax Rates: 2002-2019

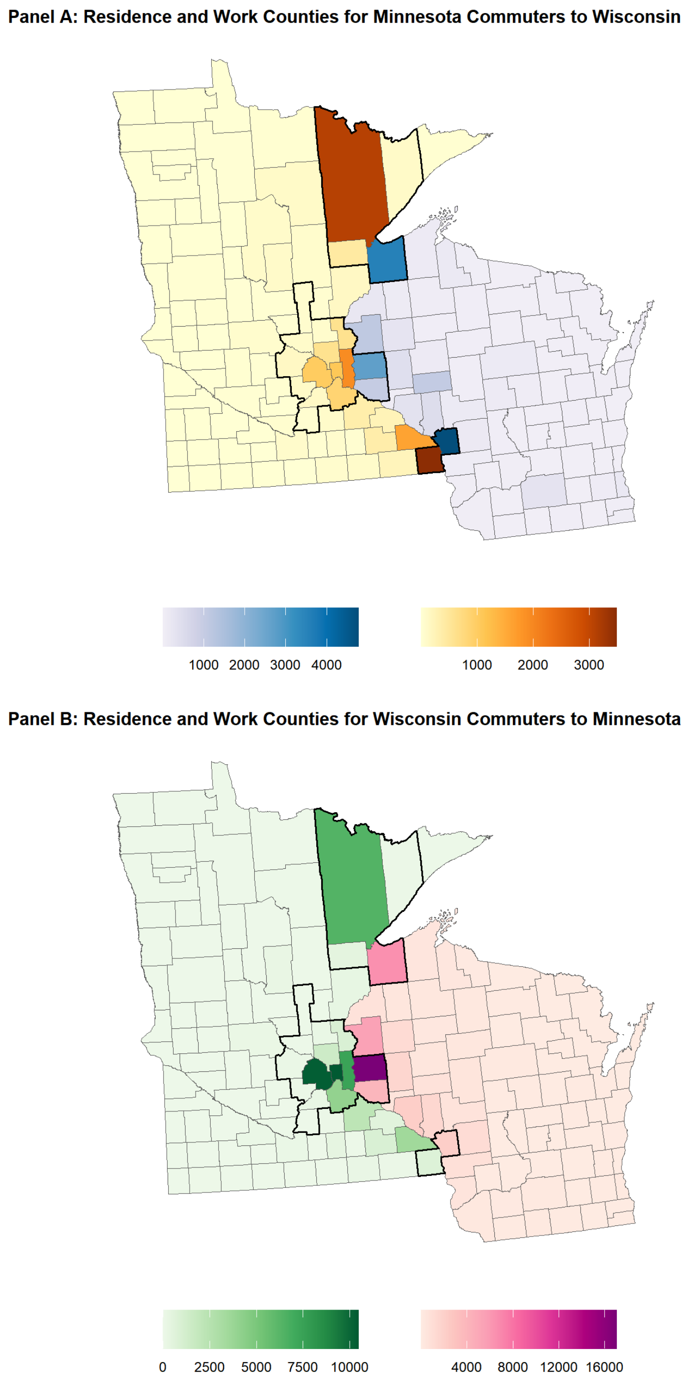


This figures shows estimated nominal average income tax rates on wage income for various income levels. Estimates are from NBER's TAXSIM (v35) calculator. Income is 91% wages, 6% dividends and 3% from taxable interest. Itemized deductions are $100 plus 2% of income for real estate taxes, $100 + 2% charitable giving and $100.01 plus 6% for mortgage interest.

The dashed vertical line in 2010 signifies repealing income tax reciprocity.

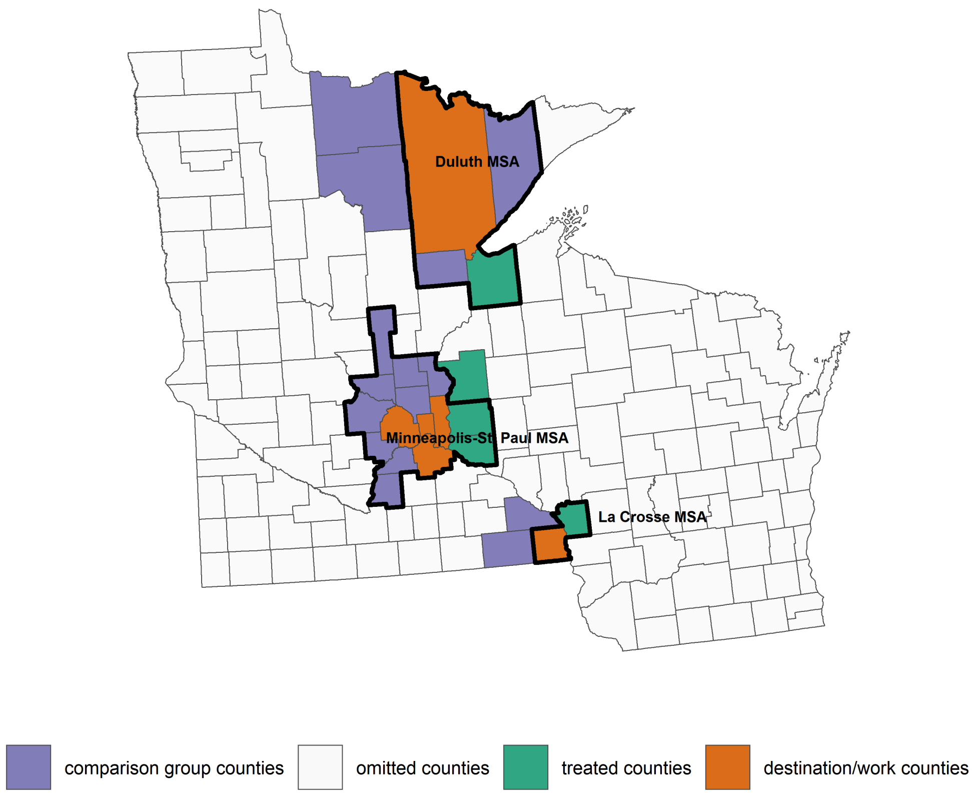
Notes: This figure shows the estimated average income tax rates in Wisconsin and Minnesota for an identical representative household at various income levels. Household characteristics were defined by the National Bureau of Economic Research (NBER). Estimation of the marginal tax rates is from NBER's Taxsim calculator (v35).

Figure 2: Spatial Distributions of Residence/Work Destinations by State: 2002-2009



Notes: This figure shows the county-level intensity of where interstate commuters in Minnesota and Wisconsin live and work. Figures reflect the annual averages from 2002 to 2009, and were tabulated from the Census Bureau's Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES) database (version 7.5). The borders of the Minneapolis-St. Paul, Duluth, and La Crosse metropolitan statistical areas, which cross state lines, are outlined by a thick black line.

Figure 3: Treatment and Same Region Comparison Group for Wisconsin's Interstate Commuters



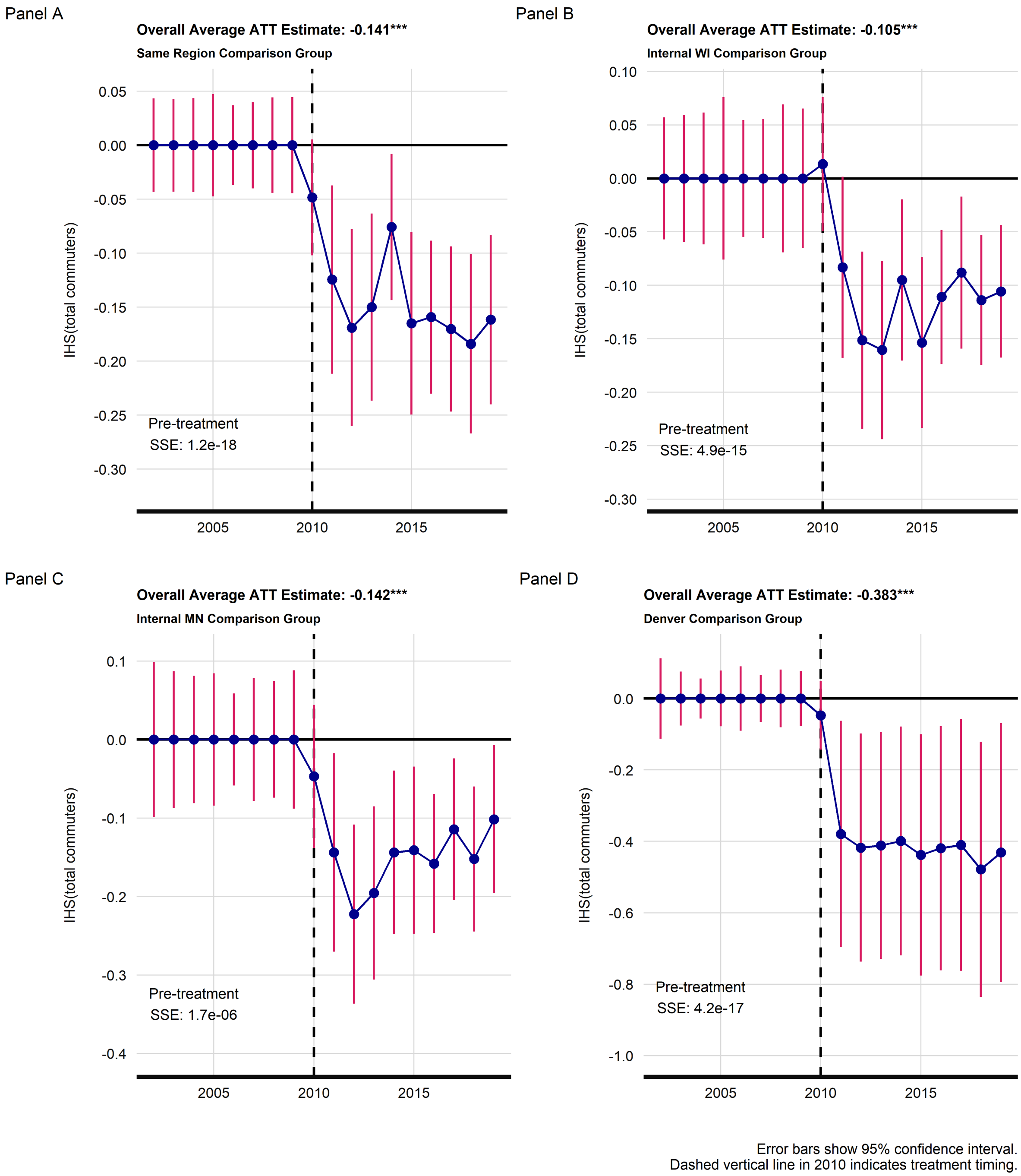
Notes: This figure shows treated, comparison, and work destination counties used in our empirical sample. The official metropolitan statistical area (MSA) borders are delineated by a dark black line. Treated Wisconsin counties are shown in green. The treatment group consists of 32 census tracts in Pierce, St. Croix, and Polk Counties in the Minneapolis-St. Paul region, 13 census tracts in Douglas County that are part of the Duluth MSA, and 25 census tracts in La Crosse County that are part of the La Crosse MSA. Comparison group counties in Minnesota are shown in purple. Comparison group commuters are individuals living in census tracts within (or contiguous to) the Minneapolis-St. Paul, Duluth, and La Crosse metro areas who cross county lines and commute to the same work counties as the Wisconsin commuters in the same region (a total of 230 census tracts).

Table 1: Descriptive Commuting Statistics by Group: 2002-2019

Group	Total Commuters	Ages 29 and under	Ages 30-54	Ages 55 and up	Low Earnings	Mid Earnings	High Earnings
WI treatment group	185.2	36.7	117.8	30.7	29.0	52.2	104.0
	(208.1)	(42.0)	(135.5)	(38.8)	(35.6)	(65.7)	(127.3)
MN treatment group	69.2	15.3	40.2	13.7	15.3	23.7	30.1
	(174.9)	(35.9)	(101.6)	(40.7)	(39.2)	(64.4)	(75.8)
WI same region comparison group	338.3	72.6	210.4	55.2	62.9	91.2	184.2
	(492.1)	(100.5)	(321.1)	(81.1)	(82.7)	(130.0)	(295.8)
MN same region comparison group	138.5	35.6	76.2	26.7	37.3	56.1	45.1
	(192.0)	(47.8)	(108.6)	(40.8)	(47.9)	(79.3)	(72.5)
WI internal comparison group	299.3	64.9	181.1	53.4	57.8	110.2	131.3
	(299.0)	(58.0)	(188.6)	(60.5)	(51.3)	(106.9)	(156.3)
MN internal comparison group	189.7	52.7	102.4	34.7	50.3	71.8	67.7
	(327.3)	(95.2)	(179.0)	(60.2)	(89.2)	(122.7)	(127.3)
Denver comparison group	500.0	102.6	302.3	95.2	91.9	164.7	243.5
	(282.2)	(66.5)	(181.9)	(57.7)	(56.0)	(113.1)	(161.7)
St. Louis comparison group	103.9	57.6	175.6	45.6	43.1	98.1	137.7
	(148.9)	(37.1)	(115.0)	(34.6)	(27.5)	(57.7)	(114.8)
Chicago comparison group	34.6	40.3	144.8	41.9	34.7	66.6	125.7
	(97.9)	(37.3)	(138.3)	(44.4)	(32.1)	(65.2)	(131.6)
Philadelphia comparison group	76.5	30.3	110.5	39.5	25.9	38.7	115.7
	(89.8)	(18.4)	(78.5)	(29.8)	(14.9)	(23.2)	(90.8)
Cincinnati comparison group	128.2	84.2	287.9	82.6	61.8	136.3	256.6
	(193.7)	(50.5)	(188.3)	(62.0)	(40.0)	(78.7)	(191.8)

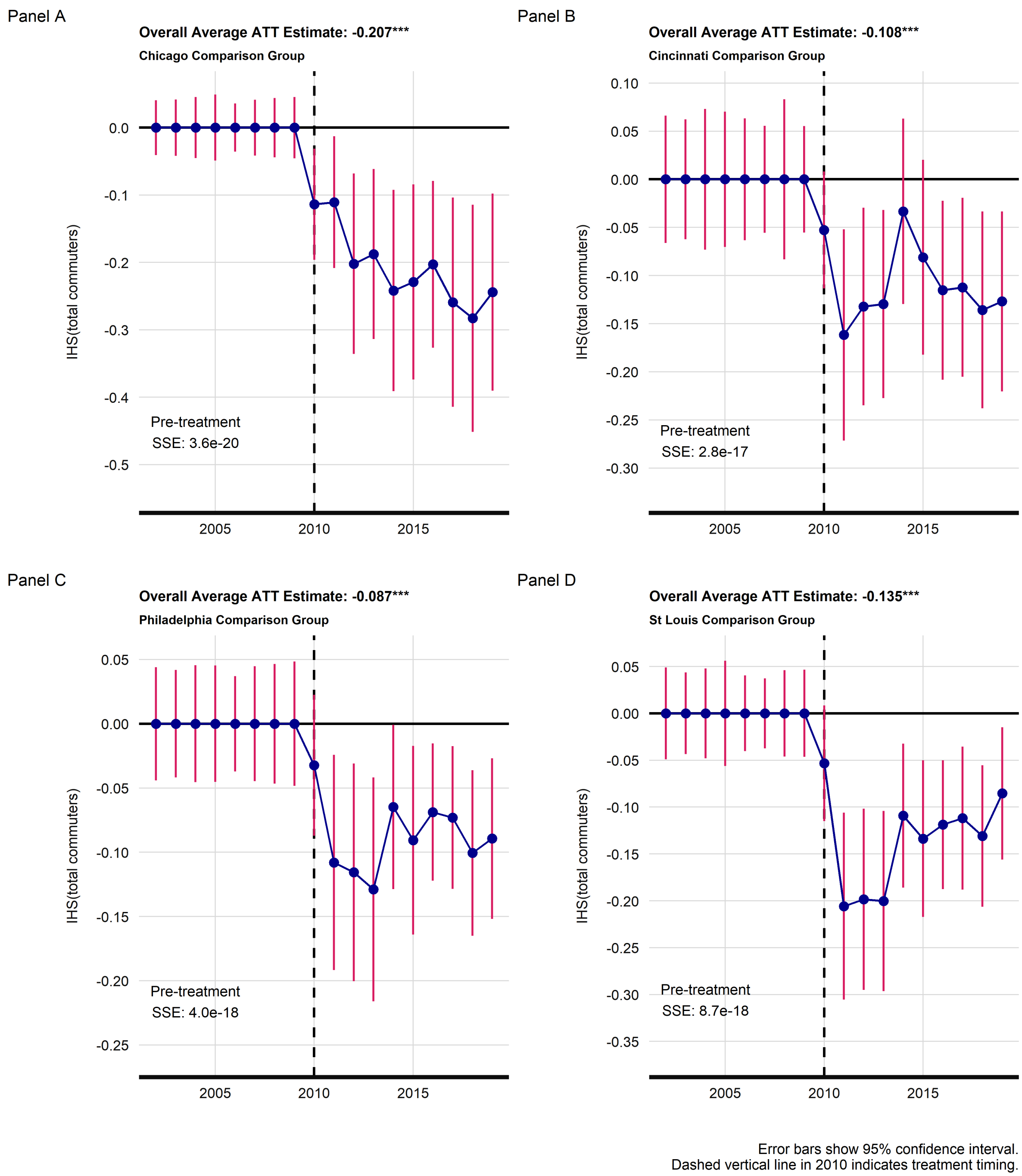
This table reports the mean number of interstate or inter-county commuters for all treated census tracts in each region from 2002 to 2019. Figures in paratheses are standard errors. See Data Appendix A for a complete description of the counties included in each region. All figures were tabulated by the authors using the Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) Location Origin-Destination Employment Statistics (LODES) data, version 7.5 (https://lehd.ces.census.gov/data/lodes). Earnings categories are defined by the Census Bureau. Low earnings is less than $1250 per month, mid earnings is between $1250 and $3333 per month, and high earnings is $3333 per month or more.

Figure 4: Wisconsin Residents Who Commute to Minnesota: Base Comparison Groups



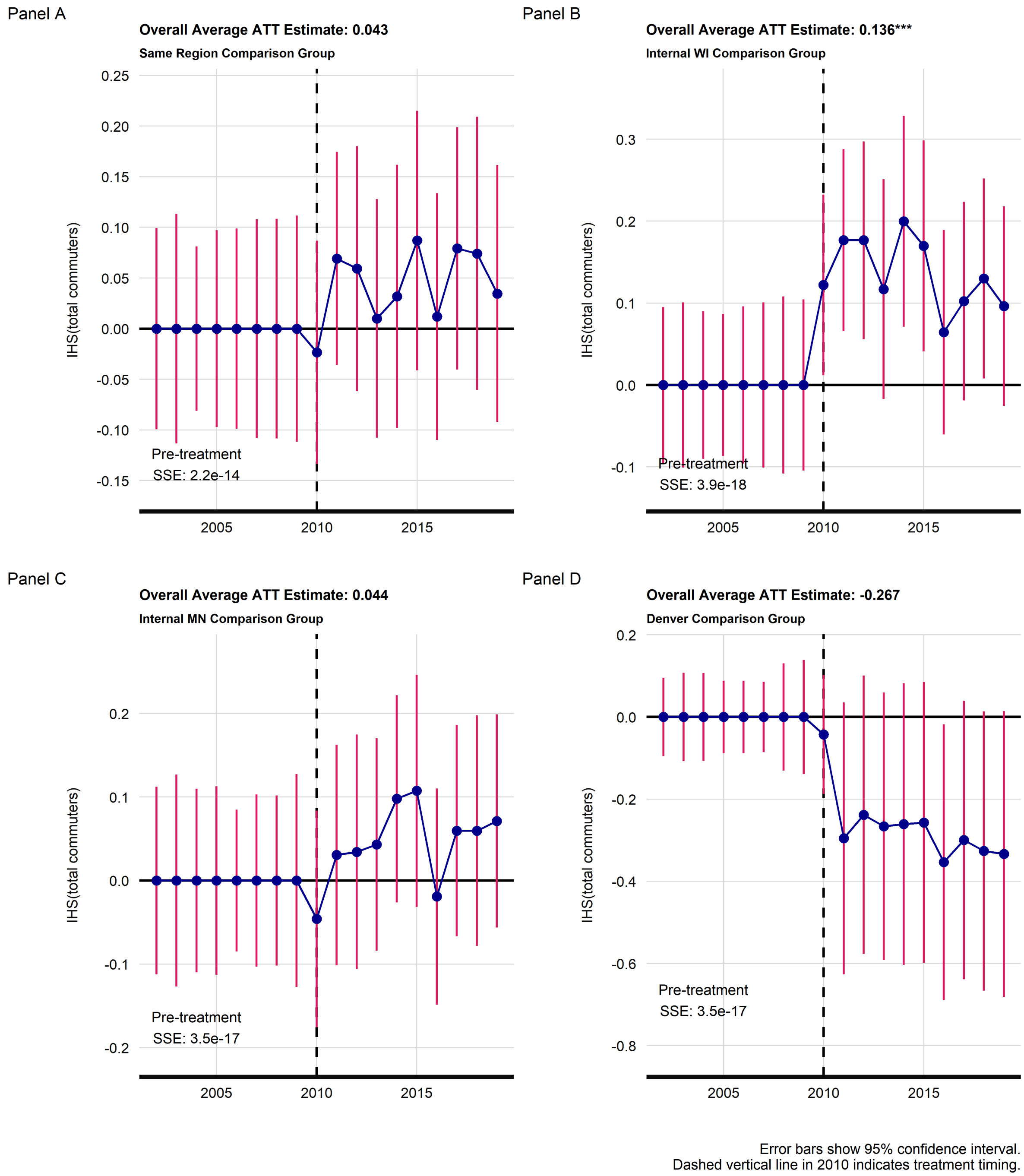
Notes: Each panel shows the average estimated treatment effect for different comparison groups. All panels match on the pre-treatment number of commuters (transformed by the inverse hyperbolic sine). Standard errors and confidence intervals were obtained via the wild bootstrap.

Figure 5: Wisconsin Residents Who Commute to Minnesota: Alternative Comparison Groups



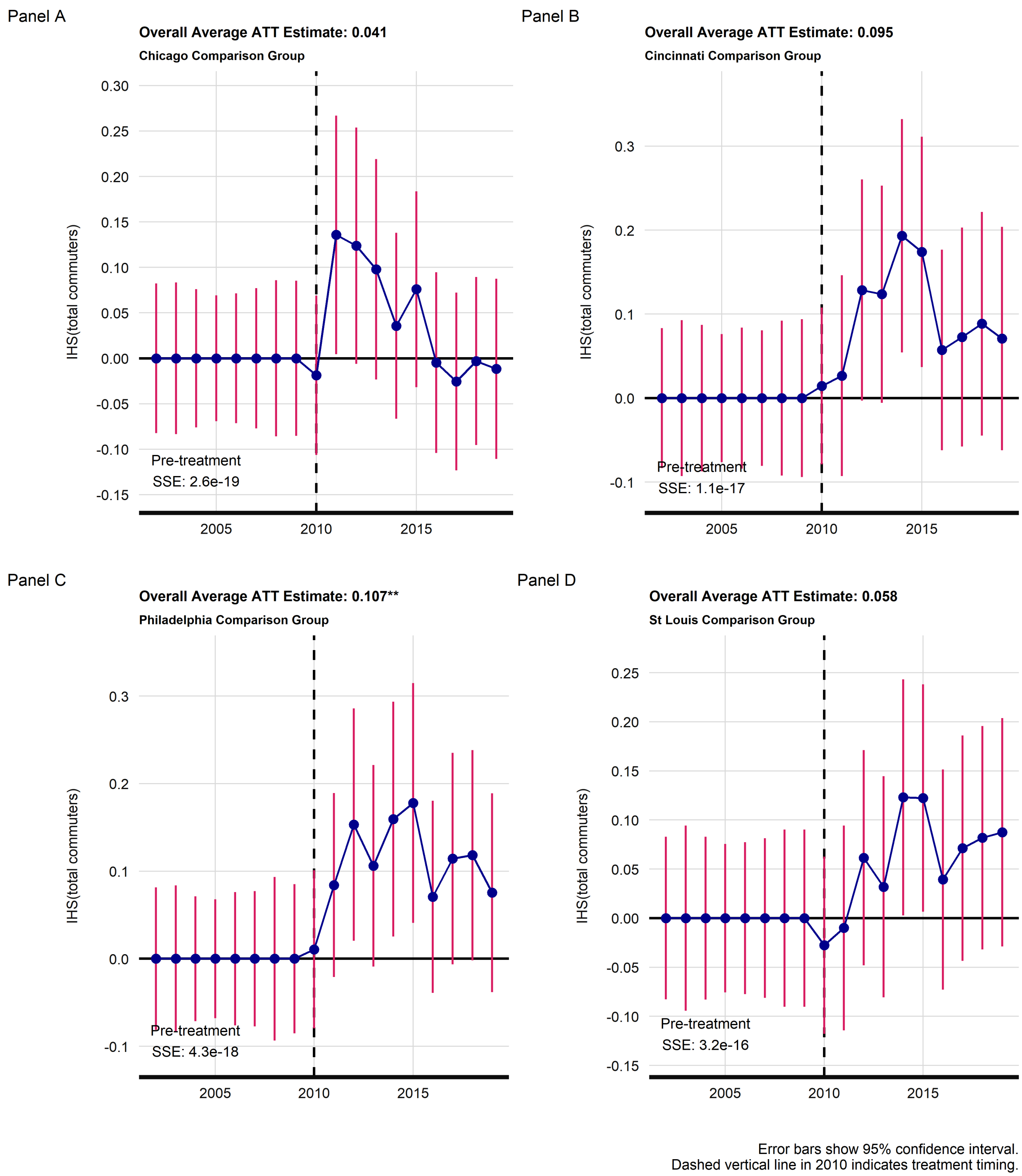
Notes: Each panel shows the average estimated treatment effect for different comparison groups. All panels match on the pre-treatment number of commuters (transformed by the inverse hyperbolic sine). Standard errors and confidence intervals were obtained via the wild bootstrap.

Figure 6: Minnesota Residents Who Commute to Wisconsin: Base Comparison Groups



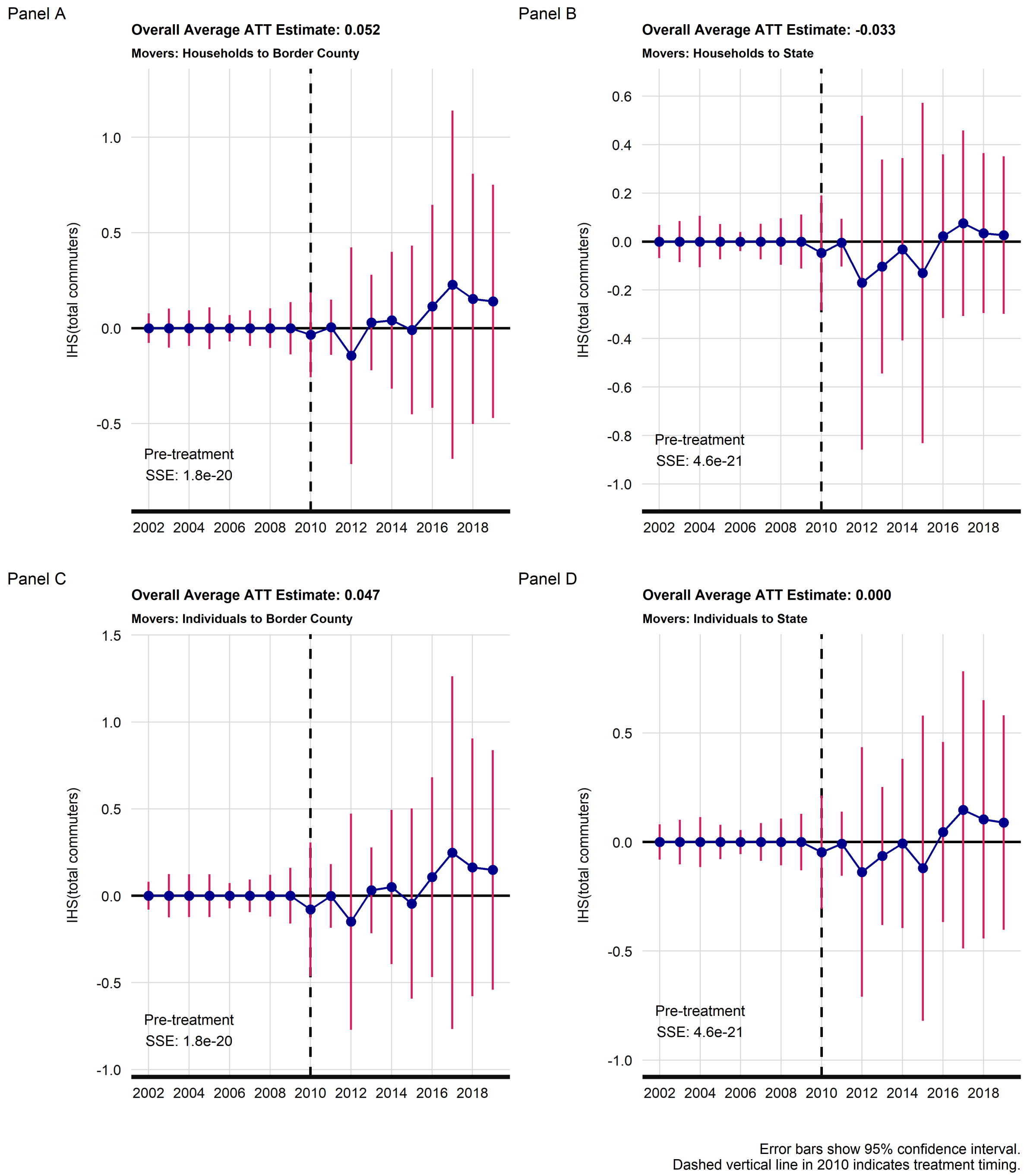
Notes: Each panel shows the average estimated treatment effect for different comparison groups. All panels match on the pre-treatment number of commuters (transformed by the inverse hyperbolic sine). Standard errors and confidence intervals were obtained via the wild bootstrap.

Figure 7: Minnesota Residents Who Commute to Wisconsin: Alternative Comparison Groups



Notes: Each panel shows the average estimated treatment effect for different comparison groups. All panels match on the pre-treatment number of commuters (transformed by the inverse hyperbolic sine). Standard errors and confidence intervals were obtained via the wild bootstrap.

Figure 8: Interstate Moves Between Minnesota and Wisconsin



Notes: Each panel shows the average estimated treatment effect for households/individuals who moved from one of the nine treated Wisconsin and Minnesota counties to the other state in year t based on Internal Revenue Service data. Panels A and B examine the number of moves (transformed by the inverse hyperbolic sine). Panel A shows results when movers are tabulated to a border county in the neighboring state, while Panel B shows results when movers are tabulated to any county in the neighboring state. Panels C and D approximate movers using the number of individuals (exemptions). Panel C reports moves to a border county, while Panel D reports moves to any county in the state. Standard errors and confidence intervals were obtained via the wild bootstrap.

Table 2: Effect of Repealing Reciprocity on Interstate Commuting by Age and Earnings

Sample subgroup	WI to MN Commuters	MN to WI Commuters
Ages 29 and under	-0.182***	0.075
Ages 30 to 54	-0.156***	0.056
Ages 55 and older	-0.068	0.047
Monthly earnings of $1250 or less	-0.107***	0.047
Monthly earnings between $1250 and $3333	-0.217***	0.075
Monthly earnings of $3333 or more	-0.097***	-0.111

This table shows the ATT estimates of the effect of repealing income tax reciprocity on interstate commuters for different age and earnings subgroups. The subgroups are the only stratification available in the Census LODES data. Each state's interstate commuters in this table are compared to their respective *same region* comparison group. *** denotes significance at the 1 percent level. Figures showing the period-by-period response are available in Appendix B.

APPENDICES

Does State Tax Reciprocity Affect Interstate Commuting? Evidence from a Natural Experiment

(*not intended for publication*)

A Data Appendix: Formation of Treatment/Comparison Groups

Commuter counts were constructed from the Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) database published by the Census Bureau. We use LODES version 7.5 and all jobs (JT00).

The number of commuters is defined as the total number of residents of census tract j in home county h who are employed in work county w at time t ($h \neq$w).

Wisconsin Interstate Commuters to Minnesota (treatment group)

Home County	Home FIPS	Number of Home Census Tracts	Work County County/State	Work FIPS	Region
Douglas	55031	13	St. Louis	27137	Duluth
La Crosse	55063	25	Houston	27055	La Crosse
Pierce	55093	8	Dakota	27037	Twin Cities
	55093	8	Hennepin	27053	Twin Cities
	55093	8	Ramsey	27123	Twin Cities
	55093	8	Washington	27163	Twin Cities
Polk	55095	10	Dakota	27037	Twin Cities
	55095	10	Hennepin	27053	Twin Cities
	55095	10	Ramsey	27123	Twin Cities
	55095	10	Washington	27163	Twin Cities
St. Croix	55109	14	Dakota	27037	Twin Cities
	55109	14	Hennepin	27053	Twin Cities
	55109	14	Ramsey	27123	Twin Cities
	55109	14	Washington	27163	Twin Cities

This treatment group captures Wisconsin residents who work in Minnesota.

Minnesota Interstate Commuters to Wisconsin (treatment group)

Home County	Home FIPS	Number of Home Census Tracts	Work County County/State	Work FIPS	Region
Carlton	27017	7	Douglas	55031	Duluth
St. Louis	27137	67	Douglas	55031	Duluth
Houston	27055	5	La Crosse	55063	La Crosse
Winona	27169	10	La Crosse	55063	La Crosse
Washington	27163	50	St. Croix	55109	Twin Cities
	27163	50	Polk	55095	Twin Cities

This treatment group captures Minnesota residents who work in Wisconsin.

Wisconsin Intrastate Same Region Comparison Group

Home County	Home FIPS	Number of Home Census Tracts	Work County County/State	Work FIPS	Region
Carlton	27017	7	St. Louis	27137	Duluth
Itasca	27061	11	St. Louis	27137	
Koochiching	27071	4	St. Louis	27137	
Lake	27075	4	St. Louis	27137	
Fillmore	27045	6	Houston	27055	La Crosse
Winona	27169	10	Houston	27055	
Anoka	27003	83	Dakota	27037	Twin Cities
	27003	83	Hennepin	27053	
	27003	83	Ramsey	27123	
	27003	83	Washington	27163	
Carver	27019	19	Dakota	27037	
	27019	19	Hennepin	27053	
	27019	19	Ramsey	27123	
	27019	19	Washington	27163	
Chisago	27025	10	Dakota	27037	
	27025	10	Hennepin	27053	
	27025	10	Ramsey	27123	
	27025	10	Washington	27163	
Isanti	27059	8	Dakota	27037	
	27059	8	Hennepin	27053	
	27059	8	Ramsey	27123	
	27059	8	Washington	27163	
Le Sueur	27079	6	Dakota	27037	
	27079	6	Hennepin	27053	
	27079	6	Ramsey	27123	
	27079	6	Washington	27163	
Mille Lacs	27095	7	Dakota	27037	
	27095	7	Hennepin	27053	
	27095	7	Ramsey	27123	
	27095	7	Washington	27163	
Scott	27139	21	Dakota	27037	
	27139	21	Hennepin	27053	
	27139	21	Ramsey	27123	
	27139	21	Washington	27163	
Sherburne	27141	11	Dakota	27037	
	27141	11	Hennepin	27053	
	27141	11	Ramsey	27123	
	27141	11	Washington	27163	
Wright	27171	17	Dakota	27037	
	27171	17	Hennepin	27053	
	27171	17	Ramsey	27123	
	27171	17	Washington	27163	

This comparison group is made up of inter-county commuters who both live and work on the Minnesota side of the three multi-state MSAs between Wisconsin and Minnesota. It is the baseline comparison group for Wisconsin's interstate commuters.

Minnesota Intrastate Same Region Comparison Group

Home County	Home FIPS	Number of Home Census Tracts	Work County County/State	Work FIPS	Region
Bayfield	55007	6	Douglas	55031	Duluth
Burnett	55013	6	Douglas	55031	
Sawyer	55113	6	Douglas	55031	
Washburn	55129	5	Douglas	55031	
Jackson	55053	5	La Crosse	55063	
Monroe	55081	9	La Crosse	55063	
Trempealeau	55121	8	La Crosse	55063	
Vernon	55123	7	La Crosse	55063	
Barron	55005	10	Polk	55095	Twin Cities
Burnett	55013	6	St. Croix	55109	
Chipewa	55017	11	St. Croix	55109	
Dunn	55033	8	Polk	55095	
Dunn	55033	8	St. Croix	55109	
Pierce	55093	8	St. Croix	55109	
Polk	55095	10	St. Croix	55109	
St. Croix	55109	14	Polk	55095	

This comparison group is made up of inter-county commuters who both live and work on the Wisconsin side of the three multi-state MSAs between Wisconsin and Minnesota. It is the baseline comparison group for Minnesota's interstate commuters.

Wisconsin Intrastate Internal Comparison Group

Home County	Home FIPS	Number of Home Census Tracts	Work County County/State	Work FIPS	Region
Clark	55019	8	Marathon	55073	Wasau, WI
Langlade	55067	6	Marathon	55073	
Lincoln	55069	10	Marathon	55073	
Portage	55097	14	Marathon	55073	
Shawano	55115	11	Marathon	55073	
Taylor	55119	6	Marathon	55073	
Waupaca	55135	12	Marathon	55073	
Wood	55141	17	Marathon	55073	
Calumet	55015	11	Winnebago	55139	Oshkosh, WI
Fond du Lac	55039	20	Winnebago	55139	
Green Lake	55047	6	Winnebago	55139	
Outagamie	55087	40	Winnebago	55139	
Waupaca	55135	12	Winnebago	55139	
Waushara	55137	7	Winnebago	55139	
Columbia	55021	12	Dane	55025	Madison, WI
Green	55045	8	Dane	55025	
Iowa	55049	6	Dane	55025	
Rock	55105	38	Dane	55025	
Sauk	55111	13	Dane	55025	

This comparison group captures intrastate commuting behavior in internal metro regions of Wisconsin that are not close to other state borders.

Minnesota Intrastate Internal Comparison Group

Home County	Home FIPS	Number of Home Census Tracts	Work County County/State	Work FIPS	Region
Benton	27009	9	Stearns	27145	St. Cloud, MN
Douglas	27041	9	Stearns	27145	
Kandiyohi	27067	12	Stearns	27145	
Meeker	27093	6	Stearns	27145	
Morrison	27097	8	Stearns	27145	
Pope	27121	4	Stearns	27145	
Swift	27153		Stearns	27145	
Brown	27015	8	Blue Earth	27013	Mankato, MN
Faribault	27043	6	Blue Earth	27013	
Le Sueur	27079	6	Blue Earth	27013	
Martin	27091	6	Blue Earth	27013	
Nicollet	27103	7	Blue Earth	27013	
Waseca	27161	5	Blue Earth	27013	
Watonwan	27165	3	Blue Earth	27013	
Cass	27021	10	Beltrami	27007	Beltrami, MN
Clearwater	27029	3	Beltrami	27007	
Hubbard	27057	7	Beltrami	27007	
Itasca	27061	11	Beltrami	27007	
Koochiching	27071	4	Beltrami	27007	
Lake of the Woods	27077	2	Beltrami	27007	
Marshall	27089	4	Beltrami	27007	
Pennington	27113	5	Beltrami	27007	
Roseau	27135	8	Beltrami	27007	

This comparison group captures intrastate commuting behavior in internal metro regions of Minnesota that are not close to other state borders.

Denver Intrastate Comparison Group

Home County	Home FIPS	Number of Home Census Tracts	Work County County/State	Work FIPS	Region
Adams	08001	97	Denver	08031	Denver, CO
Arapahoe	08005	147	Denver	08031	
Douglas	08035	61	Denver	08031	
Elbert	08039	7	Denver	08031	
Jefferson	08059	138	Denver	08031	
Weld	08123	77	Denver	08031	

Chicago Interstate Comparison Group

Home County	Home FIPS	Number of Home Census Tracts	Work County County/State	Work FIPS	Region
Lake	18089	118	Cook	17031	Chicago-IL-WI-IN
Posey	18127	33	Cook	17031	
Kenosha	55059	36	Cook	17031	
Racine	55101	44	Cook	17031	
Cook	17031	1316	IN or WI	18 or 55	
DeKalb	17037	21	IN or WI	18 or 55	
DuPage	17043	216	IN or WI	18 or 55	
Grundy	17063	10	IN or WI	18 or 55	
Kane	17089	82	IN or WI	18 or 55	
Kendall	17093	10	IN or WI	18 or 55	
Lake	17097	153	IN or WI	18 or 55	
McHenry	17111	52	IN or WI	18 or 55	
Will	17197	152	IN or WI	18 or 55	

Philadelphia Interstate Comparison Group

Home County	Home FIPS	Number of Home Census Tracts	Work County County/State	Work FIPS	Region
Burlington	34005	114	Philadelphia	42101	Philadelphia-PA-NJ
Camden	34007	127	Philadelphia	42101	
Gloucester	34015	63	Philadelphia	42101	
Salem	34033	25	Philadelphia	42101	
Bucks	42017	143	NJ	34	
Chester	42029	116	NJ	34	
Delaware	42045	144	NJ	34	
Montgomery	42091	211	NJ	34	
Philadelphia	42101	384	NJ	34	

Cincinnati Interstate Comparison Group

Home County	Home FIPS	Number of Home Census Tracts	Work County County/State	Work FIPS	Region
Dearborn	18029	10	Hamilton	39061	Cincinnati-OH-IN-KY
Franklin	18047	5	Hamilton	39061	
Boone	21015	22	Hamilton	39061	
Kenton	21117	41	Hamilton	39061	
Brown	39015	9	IN or KY	18 or 21	
Butler	39017	80	IN or KY	18 or 21	
Clermont	39025	40	IN or KY	18 or 21	
Hamilton	39061	222	IN or KY	18 or 21	
Warren	39165	33	IN or KY	18 or 21	

St. Louis Interstate Comparison Group

Home County	Home FIPS	Number of Home Census Tracts	Work County County/State	Work FIPS	Region
Jersey	17083	6	St. Louis	29189	St. Louis-MO-IL
Madison	17119	61	St. Louis	29189	
Monroe	17133	6	St. Louis	29189	
St. Clair	17163	60	St. Louis	29189	
Jefferson	29099	42	IL	17	
St. Charles	29183	79	IL	17	
St. Louis	29189	199	IL	17	

B Appendix: Robustness Checks and Additional Figures

Table B.1 compares the ATT estimates in the main paper that use $\lambda = 0$ as the regularization parameter to alternative estimates where $\lambda = 10$. These additional results are discussed in Footnote 9.

Table B.2 compares the ATT estimates in the main paper that use $\nu = 1$ to alternative estimates where $\nu = 0$. These additional results are discussed in Footnote 11.

Table 2 compares the ATTs for interstate commuters by age and income. The SCM plots corresponding to these estimates are show in Figures B.1, B.2, B.3, and B.4.

Table B.1: ATT Estimates Varying Regularization Parameter (λ)

Figure	Commute Flow	λ	Panel A	Panel B	Panel C	Panel D
4	WI $\rightarrow$ MN	0	-0.141***	-0.105***	-0.142***	-0.383***
4	WI $\rightarrow$ MN	10	-0.141***	-0.095***	-0.205***	-0.176***
5	WI $\rightarrow$ MN	0	-0.207***	-0.108***	-0.087***	-0.136***
5	WI $\rightarrow$ MN	10	-0.216***	-0.117***	-0.098***	-0.131***
6	MN $\rightarrow$ WI	0	0.043	0.136***	0.044	-0.267
6	MN $\rightarrow$ WI	10	0.104	0.181**	0.070	0.094
7	MN $\rightarrow$ WI	0	0.041	0.095	0.107***	0.058
7	MN $\rightarrow$ WI	10	0.038	0.156	0.168**	0.141

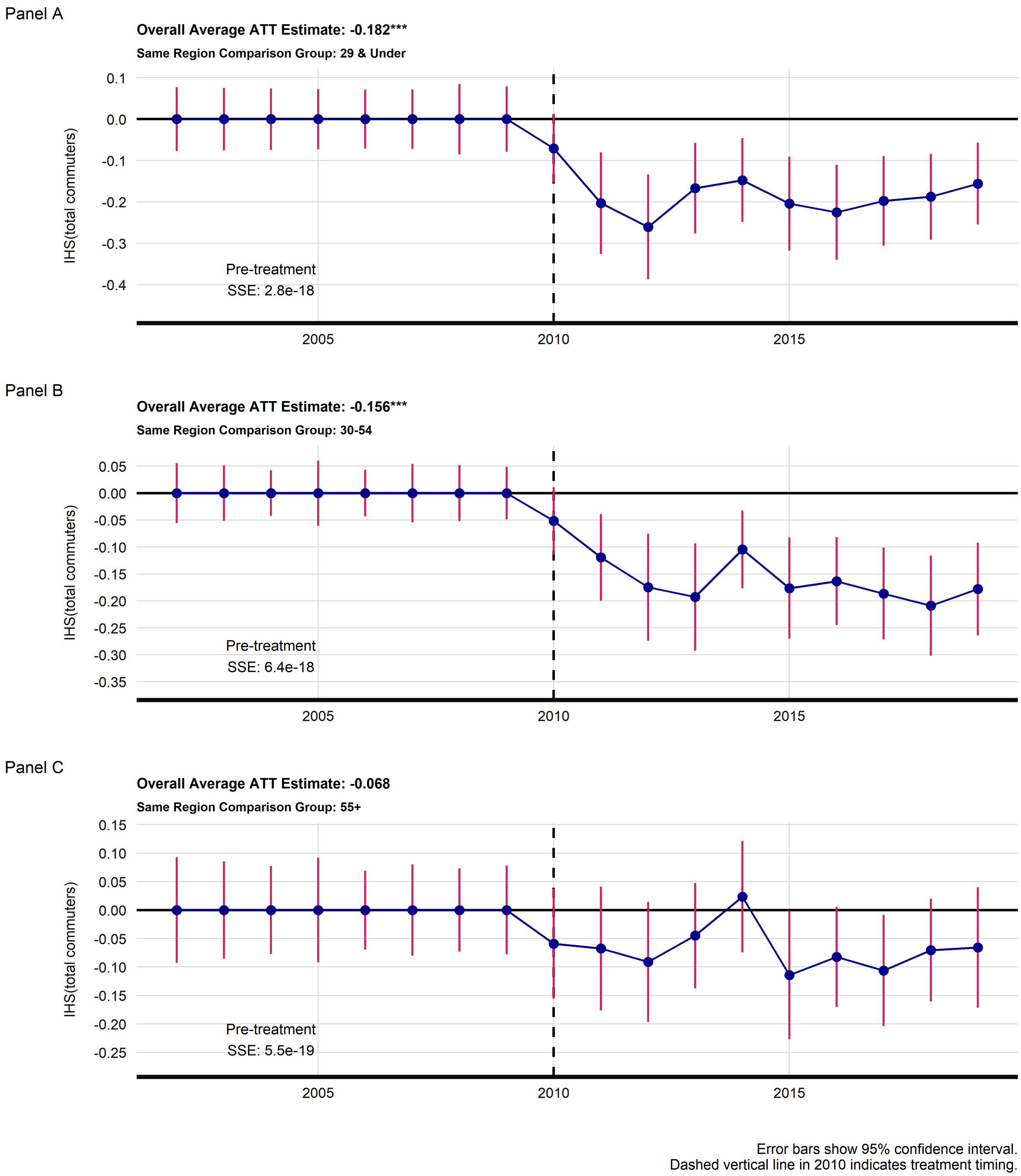
This tables compares ATT estimates when the regularization parameter (λ) varies. The results in the paper, shown in gray in this table, set $\lambda = 0$. The alternative estimates use $\lambda = 10$, which is considered to be a large value for a regularization parameter.

Table B.2: ATT Estimates Varying ν Parameter

Figure	Commute Flow	ν	Panel A	Panel B	Panel C	Panel D
4	WI $\rightarrow$ MN	1	-0.141***	-0.105***	-0.142***	-0.383***
4	WI $\rightarrow$ MN	0	-0.350***	-0.186***	-0.277***	-1.318***
5	WI $\rightarrow$ MN	1	-0.207***	-0.108***	-0.087***	-0.136***
5	WI $\rightarrow$ MN	0	-0.255***	-0.153**	-0.170***	-0.295***
6	MN $\rightarrow$ WI	1	0.043	0.136***	0.044	-0.267
6	MN $\rightarrow$ WI	0	-0.057	0.040	-0.114	-1.301**
7	MN $\rightarrow$ WI	1	0.041	0.095	0.107***	0.058
7	MN $\rightarrow$ WI	0	-0.065	0.052	0.001	-0.109

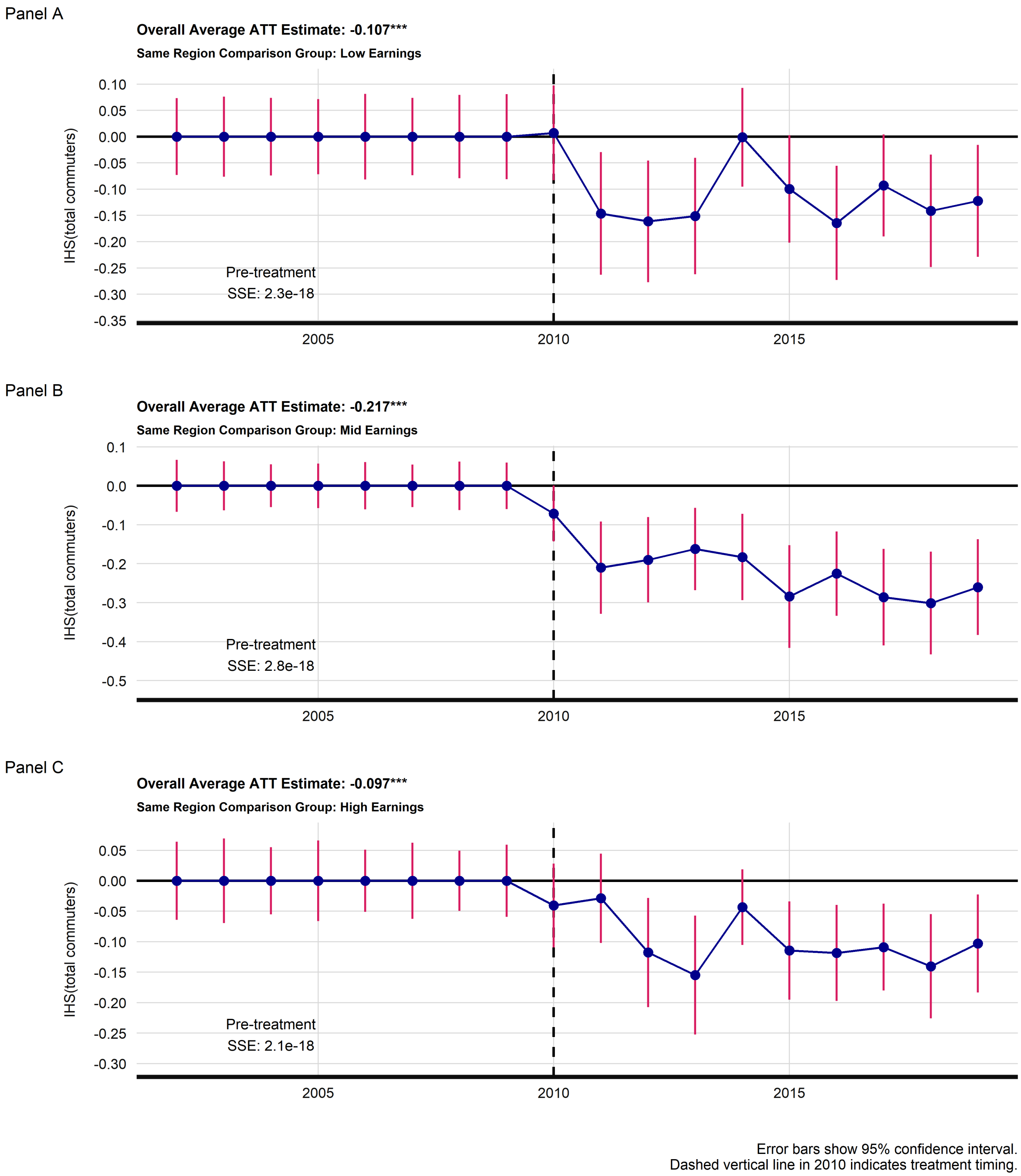
This tables compares ATT estimates when ν varies. The results in the paper, shown in gray in this table, set $\nu = 1$ and average across all units before estimating a single SCM. The alternative estimates use $\nu = 0$, which estimates a separate SCM for each treated unit and then averages them to estimate the ATT.

Figure B.1: Wisconsin Commuters to MN: Breakdown by Age



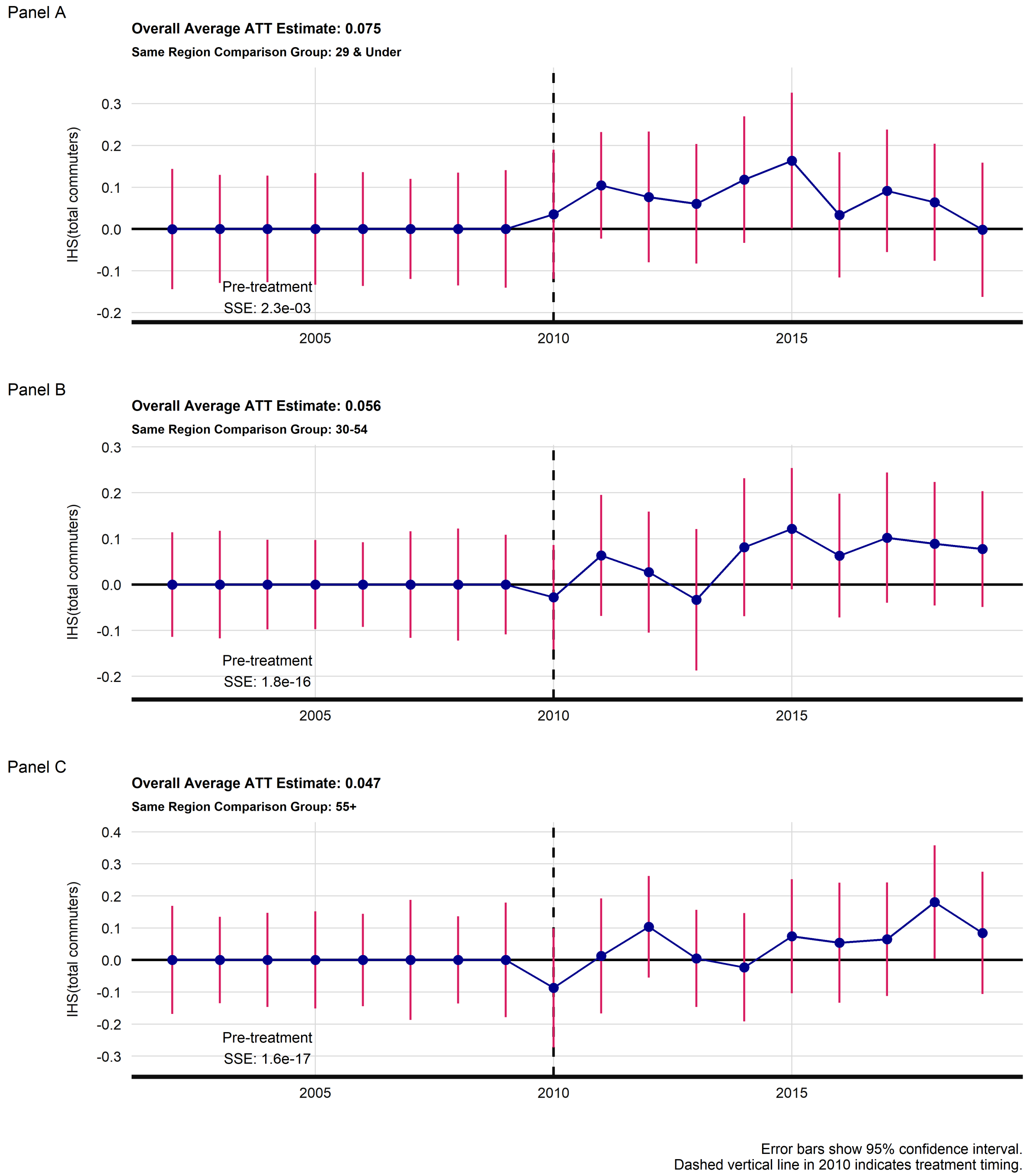
Notes: Each panel shows the average estimated treatment effect for commuters of different ages. All panels match on the pre-treatment number of commuters (transformed by the inverse hyperbolic sine). Standard errors and confidence intervals were obtained via the wild bootstrap.

Figure B.2: Wisconsin Commuters to MN: Breakdown by Income



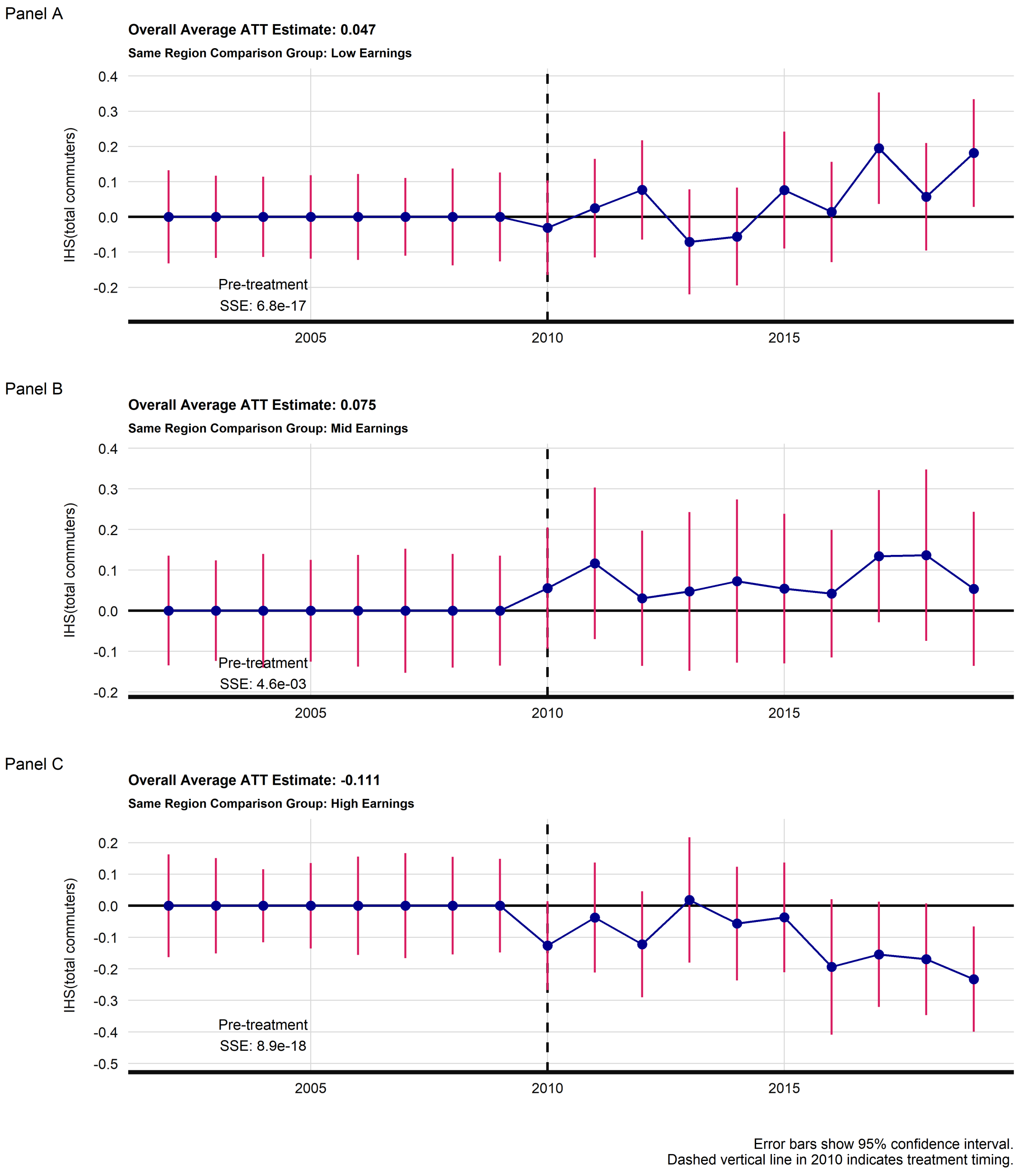
Notes: Each panel shows the average estimated treatment effect for commuters with different incomes. All panels match on the pre-treatment number of commuters (transformed by the inverse hyperbolic sine). Standard errors and confidence intervals were obtained via the wild bootstrap.

Figure B.3: Minnesota Commuters to WI: Breakdown by Age



Notes: Each panel shows the average estimated treatment effect for commuters of different ages. All panels match on the pre-treatment number of commuters (transformed by the inverse hyperbolic sine). Standard errors and confidence intervals were obtained via the wild bootstrap.

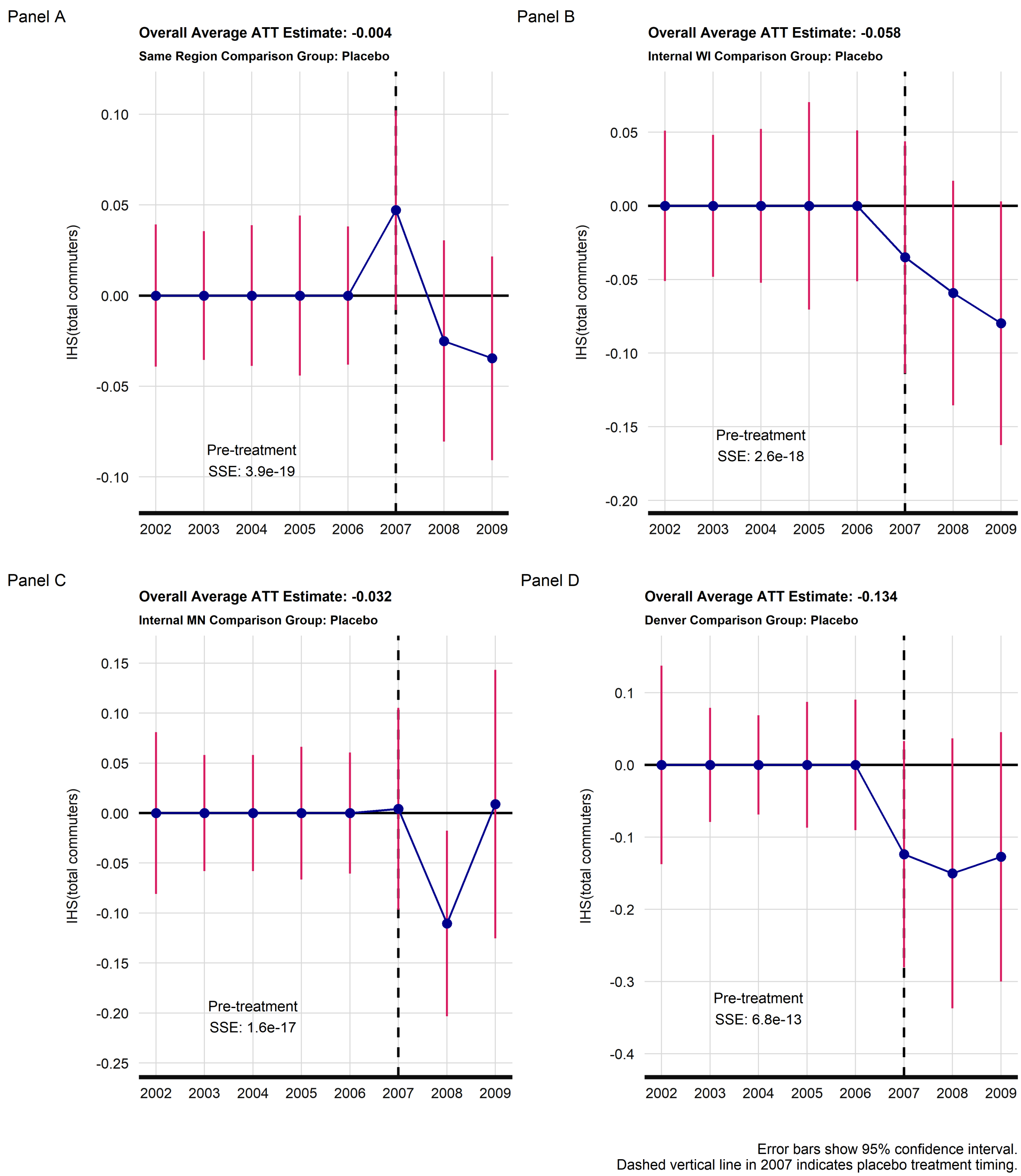
Figure B.4: Minnesota Commuters to WI: Breakdown by Income



Notes: Each panel shows the average estimated treatment effect for commuters with different incomes. All panels match on the pre-treatment number of commuters (transformed by the inverse hyperbolic sine). Standard errors and confidence intervals were obtained via the wild bootstrap.

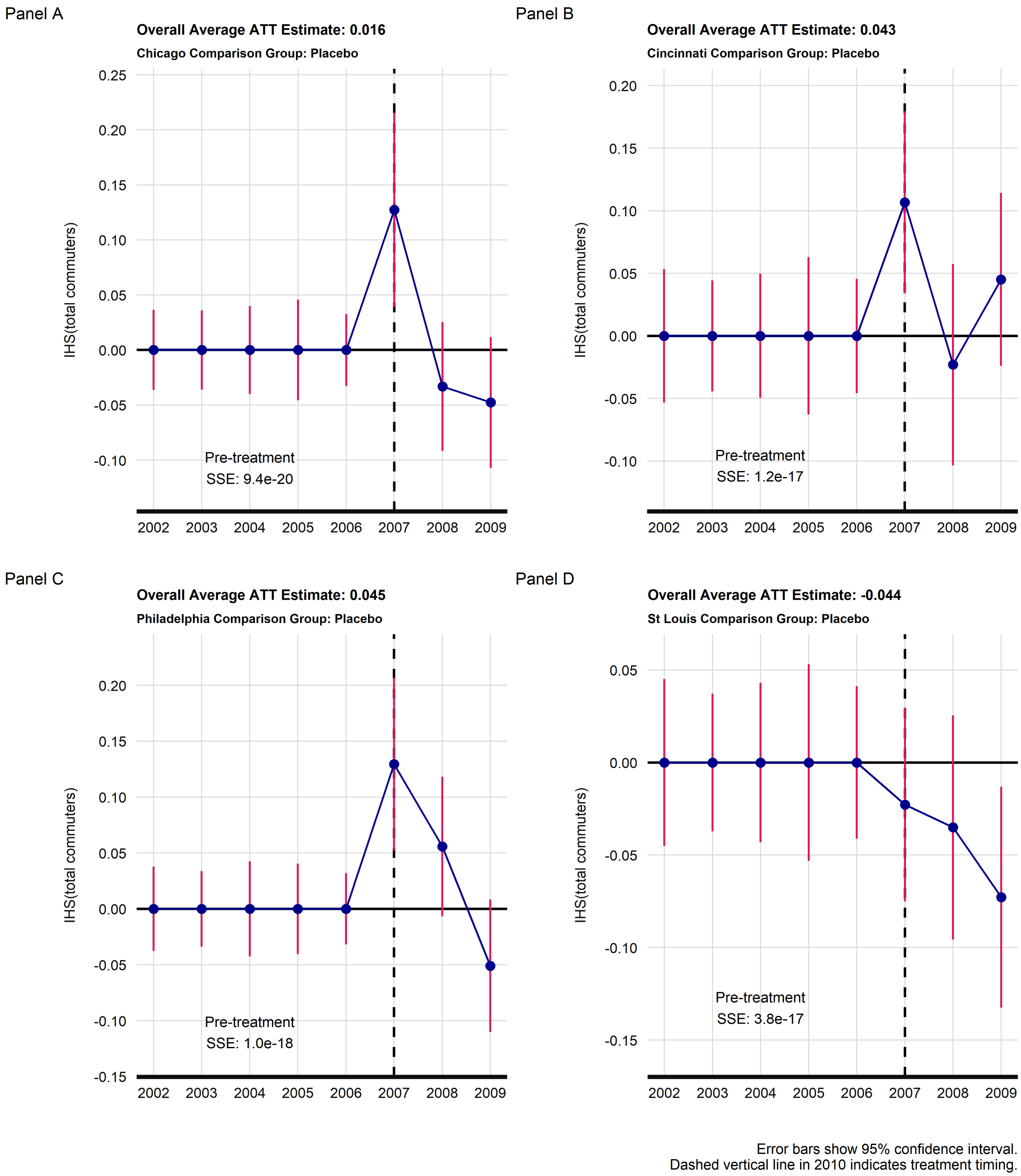
C Appendix: In-Time Placebo Tests

Figure C.1: Placebo Test of Wisconsin Commuters: Base Comparison Groups



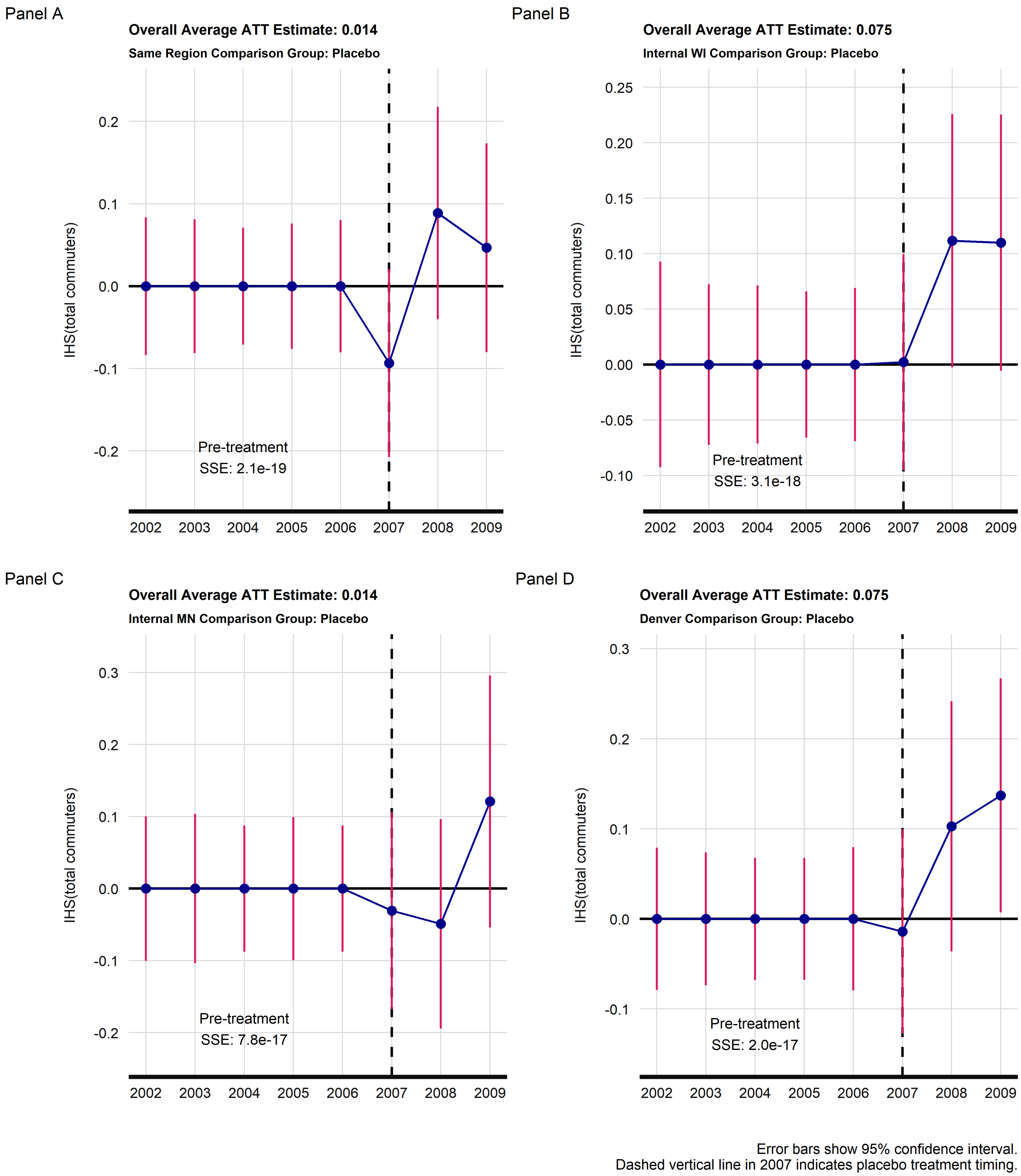
Notes: Each panel shows the average estimated treatment effect for different comparison groups using 2007 as a placebo treatment year. All panels match on the pre-treatment number of commuters (transformed by the inverse hyperbolic sine). Standard errors and confidence intervals were obtained via the wild bootstrap.

Figure C.2: Placebo Test of Wisconsin Commuters: Alternative Comparison Groups



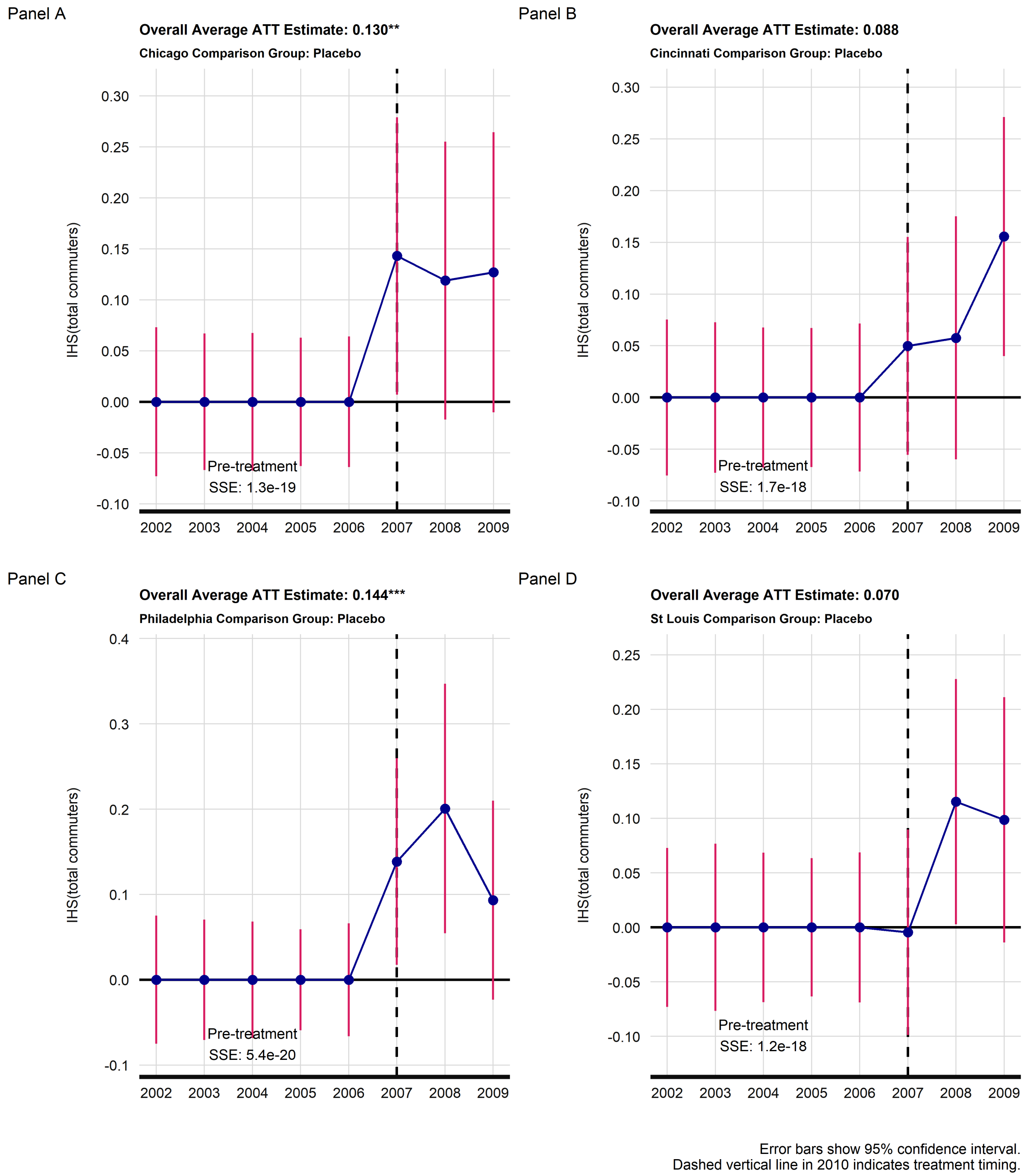
Notes: Each panel shows the average estimated treatment effect for different comparison groups using 2007 as a placebo treatment year. All panels match on the pre-treatment number of commuters (transformed by the inverse hyperbolic sine). Standard errors and confidence intervals were obtained via the wild bootstrap.

Figure C.3: Placebo Test of Minnesota Commuters: Base Comparison Groups



Notes: Each panel shows the average estimated treatment effect for different comparison groups using 2007 as a placebo treatment year. All panels match on the pre-treatment number of commuters (transformed by the inverse hyperbolic sine). Standard errors and confidence intervals were obtained via the wild bootstrap.

Figure C.4: Placebo Test of Minnesota Commuters: Alternative Comparison Groups



Notes: Each panel shows the average estimated treatment effect for different comparison groups using 2007 as a placebo treatment year. All panels match on the pre-treatment number of commuters (transformed by the inverse hyperbolic sine). Standard errors and confidence intervals were obtained via the wild bootstrap.