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ORIGINAL PAPER

Nonlinear tax-induced migration: an overlooked tale

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Abstract
The empirical literature on tax-induced migration (TIM) primarily focused on estimating the average elasticity of migration to interregional tax differentials but ignores the potential effect of the variations around this average. This paper extends the work of Moretti and Wilson (Am Econ Rev 107:1858–1903, 2017) and finds salient nonlinearity in the TIM of star scientists between 1977 and 2010. The results suggest that differences in personal income tax and research and development (R & D) tax credits between two states generate nonlinear impacts on migration; there is evidence of an important inertia range in which the differences generate little impact on migration. In contrast, the corporate income tax has approximately linear effects and investment tax credit has consistent effects only when the destination state initially has higher credits than the origin state. As different taxes or tax credits have distinctive nonlinear effects on migration, decision makers are cautioned of using average elasticities of TIM in policy making.

JEL Classification C14 · H71 · O1

1 Introduction

Tax policies are an important tool in the regional competition for skilled migrants. In the USA, many states openly compete for business activities and high-skill workers by offering lower taxes. For example, in 2013, *The New York Times* (Stewart 2013) and *Forbes* (Gregory 2013) published articles that debated whether millionaire taxpayers had fled from states with high income taxes.

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The existing literature on tax-induced migration (TIM) has mainly focused on the estimation of the average elasticity of migration to taxes but has largely ignored the variance around these estimates. For example, if TIM has a threshold pattern where migrants respond only to tax differentials outside an “inertia range,” then small-scale fiscal adjustments might not attain the policy goal of skill attraction.

This paper aims to fill this literature gap by investigating nonlinear effects of taxes on migration. Specifically, we applied a spline regression to the dataset of Moretti and Wilson (2017) and observe different nonlinear patterns in the effects of four types of taxes on scientist migration. We then use bin regression to confirm the statistical significance of observed marginal effect variations. The results suggest that personal income tax and research and development tax credit have threshold patterns in their effects on interstate migration and migration only occurred once certain thresholds in tax/credit gaps are met. The interstate gap of net-of-ATR and R & D tax credit need to be, respectively, greater than or equal to 4 and 10% points to induce migration. In contrast, corporate income tax has a linear effect on migration: a one-percent increase in tax differentials between two states leads to a fixed percentage increase in the migration flows between the two states, as described by an average elasticity. Meanwhile, investment tax credits have a stable effect on migration only when the destination state initially has higher credits than the origin state.

The rest of the paper is organized as follows. Section two reviews the empirical tax-induced migration literature, while section three presents the theoretical frameworks of tax-induced migration using spline regression. Section four discusses the data, and section five presents the empirical findings. Section six concludes the paper.

2 Literature review and motivation

Researchers have found empirical evidence for tax-induced labor migration. For example, for US domestic migration, Bakija and Slemrod (2004) found that state personal income taxes had significant impacts on the total number of the federal estate tax returns in each state. Cohen et al. (2011) identified a small but significant effect of the marginal tax rate on the net out-migration of income and people. Gius (2011) used a novel individual-level dataset to look at the effect of income taxes on the interstate migration of both whites and African-Americans at various ages. Akcigit et al. (2016) studied superstar inventors’ migration and estimated the elasticity of domestic inventors’ migration to the net-of-income-tax rate as around 0.03, while that of foreign inventors as around one. Regarding international tax-induced labor migration, Kleven et al. (2013) analyzed the labor market for professional football players across 14 European Union countries and estimated their elasticity of tax-induced migration at around 0.15. Kleven et al. (2014) showed that a Danish tax reform that lowered income taxes had doubled the number of highly paid foreigners in Denmark relative to less well-paid foreigners. An important recent development of the tax-induced migration literature is the work of Moretti and Wilson (2017). The authors separated supply-side migration from demand-driven migration. The former is individual migration that would be motivated by personal income taxes or tax credits, while the latter occurs when a corporation relocates its employees to low-tax or high-credit states. The authors estimated the elasticities of star scientists'[1] migration to personal net-of-income-tax, corporate net-of-income-tax, and corporate investment tax credit, respectively, as 1.8, 1.9, and 1.7. Research and Development tax credits were not significant.

The TIM literature to date has focused on estimating the average elasticities without considering the variation of marginal effects, implicitly assuming a linear effect. However, the marginal probability of migration might not be homogeneous under different levels of tax differences. For example, due to the individual taxpayer's incomplete information of how tax rates differ across states, an "inertia range" might exits where small interstate tax differences have no significant impact on people's migration choice. A few exceptions in the TIM literature investigated nonlinear tax-induced migration. Coomes and Hoyt (2008) found that migration between MSAs was most responsive to tax differences above a threshold level of 1.5% points and between areas that did not have reciprocity agreements.[2] However, it was not clear why they chose the 1.5 % threshold, nor was there any discussion of the marginal effects above 1.5%. Hsing (1995) and Hsing and Mixon (1996) built on the work of Cebula (1990) and identified a quadratic relationship between tax and migration. However, the papers did not fully develop theoretical frameworks for labor migration, especially the log odds ratio model that relates migration to the utility gains of different migration destinations. Moreover, no specific reason was provided to adopt a quadratic model as opposed to other models. In the broader labor migration literature, Basile and Lim (2017) found a threshold pattern in the effect of regional *wage* differentials on migration. However, the authors did not quantify how migration flows change marginally at the threshold values.

The present paper develops the research of nonlinear TIM in two ways. First, we investigate and compare the nonlinear effects of different demand- and supply-side taxes on labor migration; the findings of Basile and Lim (2017) justify an expectation of a threshold effect of individual income taxes, but corporate income taxes may still have linear effects because corporates usually have better knowledge of interregional tax differences, less liquidity constraints, and are more risk-neutral. Secondly, we did not use an ad hoc manner to choose a nonlinear model or to identify the critical points of interests because spline regression traces the marginal effects of taxes. The nonlinearity of marginal effects is further quantified with statistical significance in bin regression.

[1] Star scientists are defined as exceptional inventors that, in a given year, are at or above the 95th percentile in number of patents over the past 10 years (Moretti and Wilson 2017).

[2] Employees who live in one state but work in another only need to pay state and local taxes of his/her home state if the two states have tax reciprocity agreement.

3 Empirical migration studies and smoothing spline

This section lays out the theoretical framework of labor migration and spline regression. A logistic model and its variants have been widely used in the place-to-place labor migration literature (Gabriel et al. 1987, 1992, 1993, 1995; Sasser 2010; Kleven et al. 2013; Cohen et al. 2011). The underlying assumption is that individuals make pairwise comparisons between alternative origin–destination pairs and choose the pair that yields the highest expected utility gain from migration. The logistic migration models allow for flexible specifications to investigate and compare the effects of different migration drivers.[3] Moretti and Wilson (2017) modified the model to incorporate the impacts of income taxes or tax credits on corporate migration. Corporations have incentives to redistribute their workforce to low-tax states, and such demand-driven migration should be differentiated from supply-driven migration that might be motivated by differences in state personal income taxes. Equating demand- and supply-driven migration results in an equilibrium migration: the likelihood that an individual moved from region i to j at time t, relative to the probability of staying in that state, known as the "log odds ratio," has a linear form:

$$\log\left(\frac{P_{ijt}}{P_{iit}}\right) = \sum_{k\in\mathrm{Tax}} \alpha_k \left[\log\left(\frac{1-\pi_{kjt}}{1-\pi_{kit}}\right)\right] + \sum_{h\in\mathrm{Cred}} \beta_h \left[\log\left(\frac{\tau_{hjt}}{\tau_{hit}}\right)\right] \tag{1}$$
$$+ \gamma_i + \gamma_j + \gamma_{ij} + \gamma_t + X_{it} - X_{jt} + u_{ijt}$$

where $\log\left(\frac{P_{ijt}}{P_{iit}}\right)$ is the equilibrium log odds ratio incorporating both demand- and supply-driven migration; indices i and j, respectively, indicate the origin and destination states; k indexes two types of income taxes, average personal income tax (ATR) and corporate income tax (CIT), while h indexes investment tax credit (ITC) and R and D credits (Cred). Therefore, π_{kjt} is the destination state's personal/corporate income tax rate at time t, $1-\pi_{kjt}$ is the average net-of-income-taxes, and τ_{hjt} is the destination state's tax credits at time t. The net-of-income-tax differentials and tax-credit differentials between the origin and destination states are, respectively, represented by $\log\left(\frac{1-\pi_{kjt}}{1-\pi_{kit}}\right)$ and $\left[\log\left(\frac{\tau_{hjt}}{\tau_{hit}}\right)\right]$. Since higher net-of-income-tax and tax credits in the destination state increases migration, the coefficients α_k and β_h are expected to have positive signs. γ_i, γ_j, respectively, capture the time-invariant production and consumption amenities in the states of origin and destination; γ_{ij} indicates any time-invariant interregional differences such as climate, regional industrial compositions, or long-term housing price differentials;γ_t captures the effects of nation-wide common shocks to all states in a specific year, such as rule changes in federal tax deductibility; $X_{it} - X_{jt}$ captures the effect of time-variant regional differences on migration.

[3] For example, Sasser (2010) modified the logistics model to investigate the relative importance of three migration drivers—labor market conditions, per capita incomes, and housing affordability over time. The logistic model in Gabriel et al. (1993) allows for testing a hypothesis of asymmetric information flow between the origin and destination states.

The key identification assumption of Eq. (1) is that the differences in migration flows between two states, or a state-pair, is permanent after controlling for state-pair fixed effect γ_{ij}, year fixed effects γ_t, and region*year fixed effects γ_{ijt} (e.g., regional business cycles). In this way, the effect of *changes* in state tax-differentials on the *changes* in migration flows has a causal interpretation. Moretti and Wilson (2017) further address potential omitted-variable bias; first, they showed that the fortunes of local patent-holding companies are not systematically associated with tax changes; therefore, state governments did not alter tax policies to help underperforming local businesses, or to collect more taxes from well-performing local businesses. Secondly, the estimated impulse functions illustrated a causal relation in the time difference between the incidences of tax changes and scientist migration. The authors also ruled out the possibility of nonrandom selection. This may emerge if the origin*destination*year cells with zero mobility, which are left out of the regression, are systematically associated with tax changes.

To investigate the variation in the marginal effects of interstate tax differences on scientist migration, we augment Eq. (1) with smoothing spline terms for each of the four types of taxes. Smoothing splines are related to regression splines which first divide the range of independent variable x into K distinct regions. Within each region, a polynomial function is fit to the data. However, these polynomials are constrained to join smoothly at the region boundaries, or *knots*. Provided that the interval is divided into enough regions, the method can produce a highly flexible fit to the data. A smoothing spline is similar to a regression spline but results from minimizing a residual sum of squares (RSS) criterion augmented with a smoothness penalty as shown in (2):

$$\sum_{i=1}^{n} \left(y_i - g\left(x_i\right)\right)^2 + \lambda \int g''(t)^2 \mathrm{d}t \tag{2}$$

In Eq. (2), λ is a nonnegative parameter and the function g that minimizes (2) is known as the *smoothing spline* with some special properties [James et al. (2013)]; it is a piecewise cubic polynomial with knots at the unique values of $x_1, x_2 \dots x_n$, and has continuous first and second derivatives at each knot. Furthermore, outside of the extreme knots, g is linear.

The parameter λ determines the smoothness of fit. When $\lambda = 0$, there is no penalty of overfitting and RSS can be made zero by choosing a value of g that perfectly interpolates all observations. When $\lambda = \infty$, the optimal choice of g would be a linear function with $g'' = 0$. The slope of the linear function could be estimated by an OLS regression. The optimal of λ is chosen by *leave-one-out-cross-validation* (LOOCV) as discussed in James et al. (2013)).

The Generalized Additive Model (GAMs) provide a general framework for extending a standard linear model by allowing nonlinear functions such as smoothing spline for each of the variables separately while holding all the other variables fixed. The econometric form is:

$$\log\left(\frac{P_{ijt}}{P_{iit}}\right) = \beta_0 + \sum_{k\in\mathrm{Tax}} s\left[\log\left(\frac{1-\pi_{kjt}}{1-\pi_{kit}}\right)\right] + \sum_{h\in\mathrm{Cred}} s\left[\log\left(\frac{\tau_{hjt}}{\tau_{hit}}\right)\right] + \gamma_t + \gamma_{ij} + \gamma_{ijt} + u_{ijt} \tag{3}$$

where $s()$ is the spline term for each of the taxes or tax credits; γ_t is year fixed effect, γ_{ij} is the fixed effect for each asymmetric state-pair; γ_{ijt} is a fixed effect for each of origin-region*destination-region*year combination.

The results of the spline regression (2) are comparable to those of Moretti and Wilson (2017) because the only difference with the latter's baseline specification[4] is the replacement of linear tax (net-of-tax) terms with the spline terms. Since the replacement does not alter the causal inference arguments, the estimated smoothing splines also have the interpretation as long-run, causal effects of taxes on migration. Although it is not feasible to derive all marginal slope changes at all observations $x_1, x_2 \dots x_n$, we could plot the fitted values of smoothing spline and observe if any nonlinear patterns.

4 Data

Scientists are economically important and associated with the fostering of new industries and job creation (Zucker et al. 1998; Zucker and Darby 2006), and their interregional mobility motivates the policy and research discussions of "brain drain." Moretti and Wilson (2017) derived the longitudinal address information of star scientists, with patent counts in the top 5% of the distribution, from the COMETS patent database (Zucker et al. 2011) to compute star scientists' bilateral migration flows for every pair of states (51×51) between 1977 and 2010. The authors then joined bilateral outmigration to the origin–destination states' differential in personal and business taxes or tax credits. The probability of a scientist moving from one state to another relative to the probability of staying at the origin state is the outmigration odds-ratio, as discussed in section three. Potentially, there were 84,150 origin*destination*year cells but only 15,247 of them have positive migration flows.

The data contains information on four types of taxes or tax credits. Individual income average tax rate (ATR) is the average tax burden of a potential star scientist in a state. Since the COMET dataset did not provide income information, star scientists have been assumed to be among top 1% income earners in the USA. In some states, federal income taxes can be deducted from state income taxes but in other states they cannot. To account for such interaction between federal taxes and state income taxes, the authors used total ATR instead of mere statutory state income taxes. Corporate income tax rates (CIT) in each state were the effective rates that were also adjusted for the deductibility of state taxes on federal corporate tax returns or vice versa (Chirinko and Wilson 2008). Investment tax credit (ITC) is a credit against corporate income tax that encourages companies to locate more of its properties and payroll in a state; therefore, it is assumed that these credits will impact the demand-side migration of scientists when the company relocates its staff to a

[4] Specification (6) of Table 2a) in Moretti and Wilson (2017) has provided the baseline regression results. It was the preferred specification among a variety of models controlling for state fixed effects, state-year fixed effects (state-specific time trends) or region-year fixed effects (region-specific time trends).

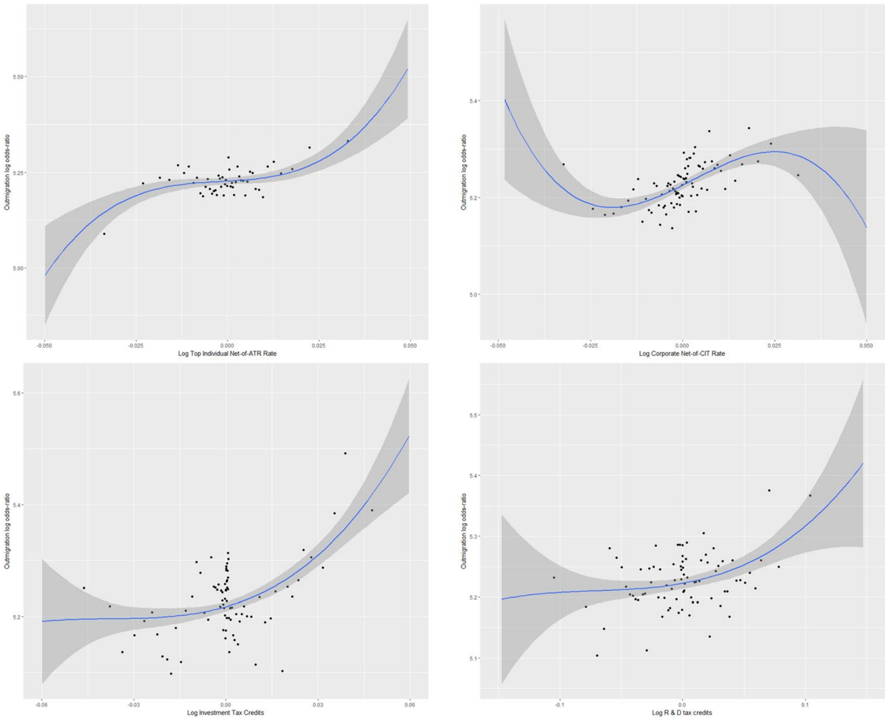

Fig. 1 Bin-scatter plots of outmigration to taxes. *Note*: In this figure we show four bin-scatterplots of the log-odds ratio against the log net-of-tax rates controlling for state-pair and year fixed effects, in the same fashion as figure 4 in Moretti and Wilson (2017) but with more bins. To show the trend, we also plot B-splines with 3 degrees of freedom between the outmigration log odds ratio and each of the tax or tax credits. The top left panel shows that in close proximities of the y-axis, the outmigration between a given origin–destination pair does not vary significantly to the changes in the net-of-ATR rate in the origin state, but the effect increases when the net-of-tax diverges from zero. The top right panel shows a linear relationship between CIT and outmigration except at outer ranges of net-of-CIT differentials, but the confidence intervals at outer variable values are too wide for a meaningful interpretation. The bottom left panel has an asymmetric pattern across the y-axis: an upward trend emerges under positive initial destination-origin credit differentials, but outmigration does not seem to vary under negative credit differentials. The last panel also shows such asymmetric pattern across the y-axis between outmigration and R and D research credits

state offering higher investment credits. In contrast, Research and Development tax credits can be offered to both individuals (against individual income taxes) and corporations (against corporate income taxes); in this case, the impacts will be on both demand- and supply-side migration.

In Fig. 1, we show four bin-scatterplots of the log-odds ratio against the log net-of-tax rates controlling for state-pair and year fixed effects, in the same fashion as

Table 1 Spline regression results

	edf	Ref.df	F	p value
s(ATR)	7.556	8.531	6.83	2.02e−09 ***
s(CIT)	8.265	8.871	6.839	7.82e−10 ***
s(ITC)	8.332	8.877	13.732	< 2e−16 ***
s(R and D cred)	8.765	8.981	9.697	4.73e−14 ***

$n = 15{,}226$, R-sq.(adj) = 0.825, Deviance explained = 85%. The first two columns are the values of *equivalent degrees of freedom*, or the most suitable degrees of polynomials to approximate the spline term. The third column is the F-statistics, and the fourth column is the p values associated with a linear null hypothesis

Fig. 4 in Moretti and Wilson (2017) but with more bins.[5] To show the trend, we also plot B-splines with 3 degrees of freedom between the outmigration log odds ratio and each of the tax or tax credits. The top left panel shows that in close proximities of the y-axis, the outmigration between a given origin–destination pair does not vary significantly to the changes in the net-of-ATR rate in the origin state but the effect increases when the net-of-tax diverges from zero. The top right panel, in contrast, shows a linear relationship between CIT and outmigration except at outer ranges of net-of-CIT differentials, but the confidence intervals at outer variable values are too wide for a meaningful interpretation. The bottom left panel has an asymmetric pattern across the y-axis: an upward trend emerges under positive initial destination-origin credit differentials, but outmigration does not seem to vary under negative credit differentials. The last panel also shows such asymmetric pattern across the y-axis between outmigration and R & D research credits. Altogether, Fig. 1 provides preliminary evidence[6] of different relationships between outmigration and net-of-taxes or tax credits, motivating a deeper investigation of potential effect variations.

5 Empirical results

Table 1 summarizes the result of fitting the spline augmented GAM in Eq. (3). Each of the four p values corresponds to a null hypothesis of a linear relationship versus the alternative of a nonlinear relationship (James et al. 2013). The significance levels provide clear evidence that all four taxes or tax credits have nonlinear effects on scientist migration.

[5] Figure 4 in Moretti and Wilson (2017) show a series of bin-scatterplots of the log odds ratio against the log net-of-tax rate after demeaning the log odds ratio and the log net-of-tax rates by their within-pair and within-year sample means. They used 40 bins sorted along the x-axis, here in this paper we use 80 bins.

[6] The B-splines only illustrate the one-to-one partial relationship between outmigration and each tax, leaving the effects of other taxes out of consideration. Additionally, the choice of B-spline with three degrees of freedom is ad hoc. In contrast, generalized additive model (GAM) with smoothing spline terms does not require manual choices of degrees of freedom and simultaneously incorporates all taxes.

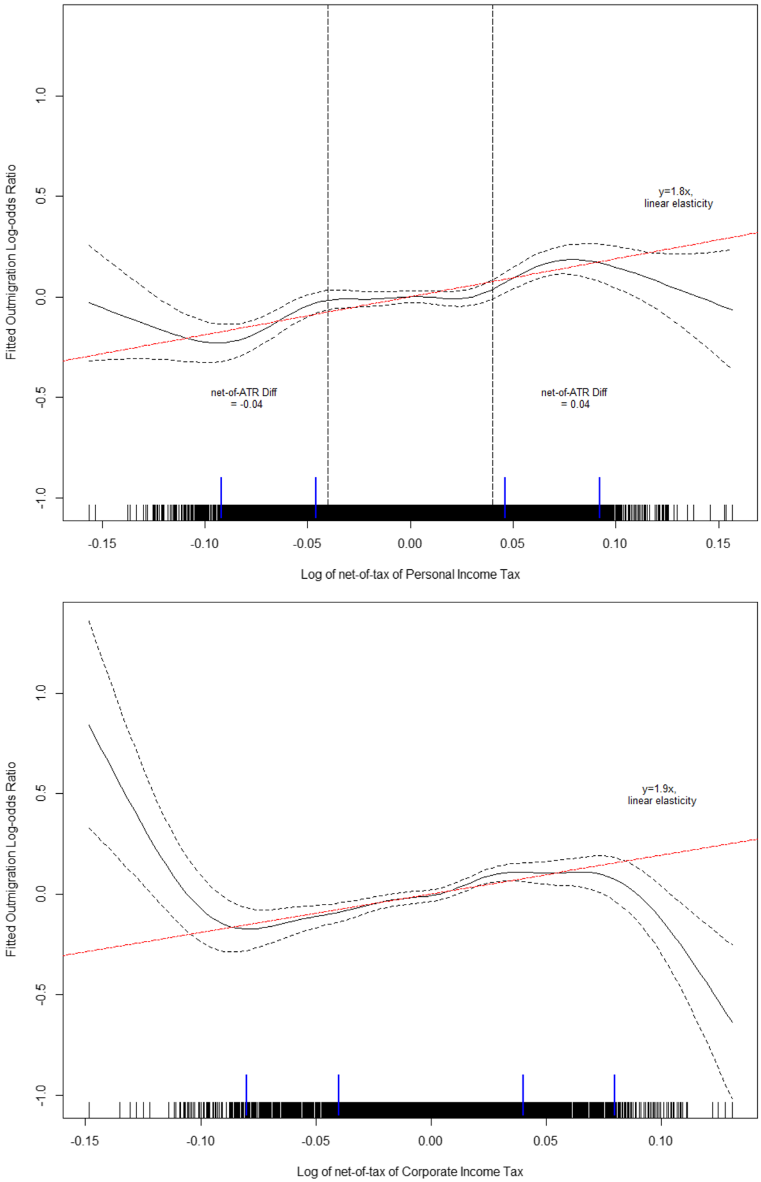

Fig. 2 Smoothing splines of personal and corporate income taxes. *Note*: The vertical axis reports the scale of the expected values of the log odds ratio; the horizontal axis reports the scale of the log of inter-regional tax differentials. The red dotted lines display the average elasticities estimated in Moretti and Wilson (2017). The blue solid tick marks are indicators of one and two standard deviations of the tax differences from zero. The wide confidence intervals at the outer range of tax differentials are typical of spline regression (James et al. (2013)). The upper panel displays a clear threshold pattern: the slope of the fitted value curve increases more rapidly after a 4% differential is reached. The lower panel shows a mainly linear effect on migration throughout most of the range of CIT

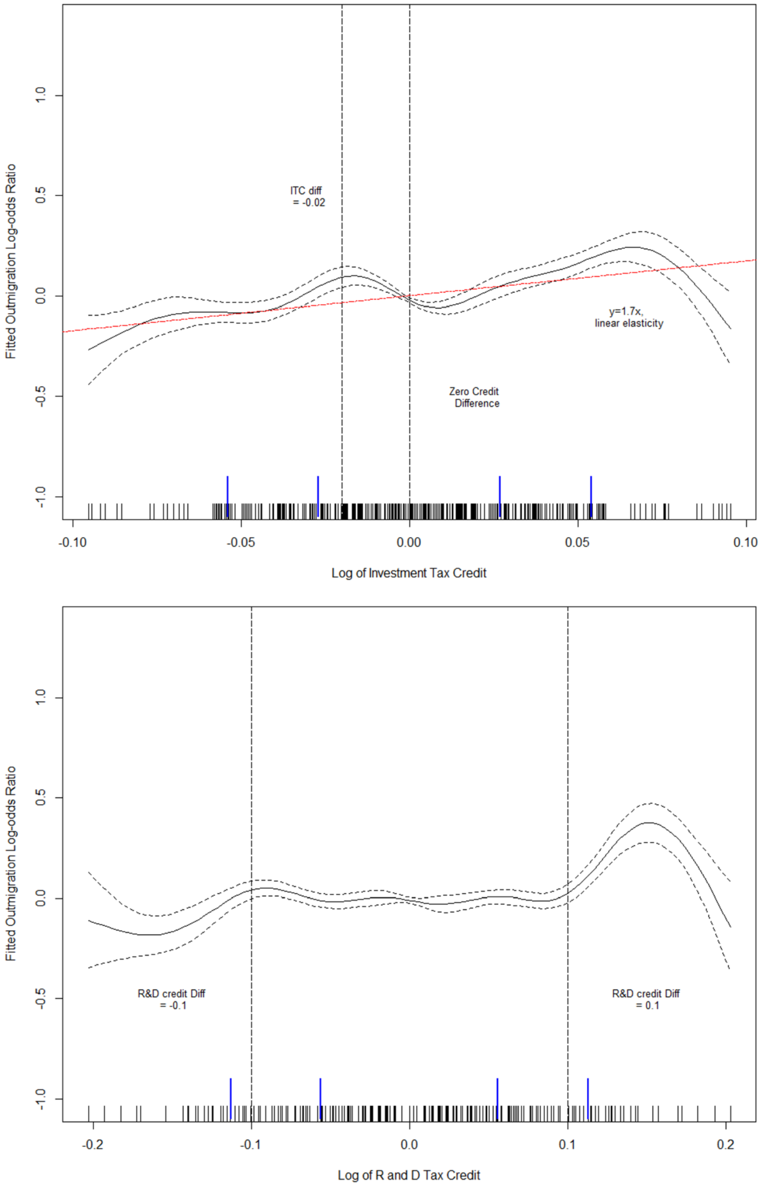

Fig. 3 Smoothing splines of corporate investment, R and D Tax Credits. *Note*: The vertical axis reports the scale of the expected values of the log odds ratio; the horizontal axis reports the scale of the log of interregional tax differentials. The red dotted lines display the average elasticities estimated in Moretti and Wilson (2017). The blue solid tick marks are indicators of one and two standard deviations of the tax differences from zero. The upper panel shows that ITC has a stable linear effect only when initially there is higher tax credit in the destination state than in the origin state; the lower panel of Fig. 3 shows that the R and D tax credit also has a threshold pattern like net-of-ATR but with greater thresholds: credit differential impacts migration only when it exceeds 10%

Table 2 Interaction augmented full sample regression

	(1)	(2)
ATR, 99th Perc. (1 – atr)	1.93***	0.10
ATR * 1(ATR ≥ 0.04)	–	1.84***
ATR * 1(ATR ≤ −0.04)	–	1.57***
State CIT (1 – cit)	1.89***	1.55***
CIT * 1(ITC ≥ 0)	–	0.17
State ITC (1 + itc)	1.80***	− 9.89***
ITC * 1(ITC ≥ 0)	–	12.66***
ITC * 1(ITC ≤ −0.02)	–	10.79***
R and D credit (1 + cred)	0.4**	− 0.21
Cred * 1(Cred ≥ 0.1)	–	1.82***
Cred * 1(Cred ≤ −0.1)	–	0.97***
Origin * destination pair FE	Yes	Yes
Year FE	Yes	Yes
Origin and destination pair region * year FE	Yes	Yes

Each column is from a separate regression. Column (1) is the baseline results of Moretti and Wilson (2017). Standard errors are corrected with three-way clustering by origin-state*year, destination-state*year, and state-pair. All regressions include year fixed effects, and have 15,226 observations. *$p<0{:}10$, **$p<0{:}05$, ***$p<0{:}01$

Figures 2 and 3 show the fitted smooth functions alongside their confidence intervals for the four taxes and compare them with the elasticities estimated in Moretti and Wilson (2017). The vertical axis reports the scale of the expected values of the log odds ratio; the horizontal axis reports the scale of the log of interregional tax differentials. The red dotted lines display the average elasticities estimated in Moretti and Wilson (2017). The wide confidence intervals at the outer range of tax differentials are typical of spline regression (James et al. (2013)). The upper panel of Fig. 2 displays a clear threshold pattern: the slope of the fitted value curve, and thus, the marginal effect of net-of-tax differentials, increases more rapidly after a 4% differential is reached. On the other hand, the lower panel of Fig. 2 shows a mainly linear effect on migration throughout most of the range of CIT. The upper panel of Fig. 3 shows that ITC has a linear effect when there is higher tax credit in the destination state than in the origin state, but the effects vacillate between positive and negative values without clear interpretation when the origin state initially had higher tax credits; the lower panel of Fig. 3 shows that the R and D tax credit also has a threshold pattern like net-of-ATR but with greater thresholds: credit differentials impact migration only when they exceed 10%.

Figures 2 and 3 present the general nonlinearity patterns of the taxes but do not quantify marginal effect changes. Table 2 uses bin regression on the full sample to fill this gap. Column (1) replicates the baseline results reported in table 2a column six of Moretti and Wilson (2017), while column (2) augments the baseline specification with interaction terms corresponding to nonlinear effects.[7]

The interpretations of Figs. 2, 3, and Table 2 are compatible with those of the linear average elasticities, but the latter glosses over important effect variations. For ATR, a 4% net-of-tax differential would not induce changes in migration flows. However, when the ATR net-of-tax is 4% or higher in j than in i, an additional 1% increase in after-tax income in j is associated with a 1.84% increase in the net flow of star scientist moving from i to j. On the other hand, when the net-of-tax is 4% lower in j than in i, an additional 1% in after-tax income in j would induce a 1.57% migration flow from i to j. The effect of CIT does not have an inertia range and an additional 1% increase in net-of-tax in j would linearly induce a 1.55% migration flow increase from i to j, regardless of the sign and magnitude of the original net-of-tax differential of j relative to i.

The nonlinearity of ITC has an asymmetric pattern: if the net-of-tax is originally higher in j, then a 1% increase in j's credit would result in a 2.77% increase in the migration flow from i to j. The effect is linear without an inertia range, meaning that the 2.77-percent migration increase occurs regardless of the magnitude of the initial j to i net-of-tax differential. However, if j originally has lower credit than i and the 1% credit-increase only narrows the gap, then the migration flow from i to j may either increase or decrease due to the credit-increase in j, depending on whether the initial credit difference exceeds -0.02. R & D research credit has a similar threshold pattern as ATR: the inertia range is between -0.1 and 0.1 and the migration responses are, respectively, 1.82% and 0.97%, respectively, when state j originally had higher or lower credits.

6 Conclusion

The average elasticities of labor migration to interregional tax differences estimated in the previous literature have potentially important variance effects. This paper extends Moretti and Wilson (2017) and finds different nonlinear effects for four types of taxes or tax credits on migration. The effects of personal income taxes and research and development tax credit have threshold patterns, meaning that the migration flows of scientists only respond to net-of-tax or credit differentials that are outside the "inertia ranges." The interstate differentials of net-of-ATR and R & D tax credit need to be, respectively, greater than or equal to 4 and 10% points to induce migration. Corporate income taxes have an overall linear effect; migration flows have a stable response to CIT changes and raising the net-of-tax in the destination state attracts migrants from other states regardless of the initial net-of-taxes differentials. Corporate investment credits have consistently positive effects on migration

[7] The smoothing splines display changes of marginal effects at ± 0.04 for ATR, zero for ITC, ± 0.1 for R and D credits, and no change for CIT. Therefore, for the bin regression, we interact ATR with the indicator functions $1(\text{ATR} \geq 0.04)$ and $1(\text{ATR} \leq -0.04)$, as well as CIT/ITC with $1(\text{CIT/ITC} \geq 0)$. ITC is further interacted with $1(\text{ITC} \leq -0.02)$. R and D credit is interacted with $1(\text{Cred}) \geq 0.1$ and $1(\text{Cred} \leq -0.1)$
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only when the destination state initially had higher tax credits than the origin state. In other words, raising tax credits in the destination state would not consistently attract migrants from other states that have a higher level of tax credits. Meanwhile, it is important to stress again that the data did not provide patent holders' income, but their combined salary and capital gains income were assumed to be in the top 1% in the nation. Therefore, we cannot investigate how differences in income might lead to different responses for a given difference in tax rates. For future studies without this data limitation, the investigation of the combination of nonlinearities in both income and tax differences might provide new findings on migration behaviors.

Contemporary regional competition often features fiscal strategies to attract highly skilled workers and business activities that are critical to local technological innovation and economic growth. Therefore, it is vital to understand how fiscal tools truly impact migration. As taxes have nonlinear impacts on migration, decision makers need to be cautious about the use of the average TIM elasticities estimated in the previous literature in policy making. As with other forms of migration, this paper has revealed some important inertia ranges in tax differentials. Hence, a state attempting to adjust tax rates needs to consider not just the opportunity cost of lost revenue (due to the downward adjustment of tax rates), but the probability that the anticipated in-migration of skilled workers/businesses will occur.

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