Immigration is central to recent discussions of American public policy. The most recent manifestation of the conversation being the role of high skill labor in innovative industries and the H-1B Visa program (Mac and Bensinger, 2024). Despite the existence of a large literature studying the effects of immigration on labor market outcomes, there is a dearth of research regarding immigration's effects on total factor productivity (CBO, 2023). In this proposal I ask what the shorter and longer run effects of immigration on total factor productivity (TFP) are. I first develop a simple conceptual framework which shows that immigration may help or hurt TFP. The framework also allows for a meaningful interpretation of the estimated effects I present here in addition those of the rest of the literature. In particular, the framework helps reconcile the seemingly conflicting evidence on the relationship between immigration and TFP reported in the small literature studying the topic.[1] To develop my preliminary evidence, I use the local projections instrumental-variables (LPIV) estimator (Jordà and Taylor, 2024; Ramey, 2016) to estimate dynamic causal effects of immigration on TFP. In particular, I show that a US state which experiences a 1 percentage point increase in the flow of immigration as a percentage of its population experiences a persistent increase in measured TFP growth of about 1 percentage point for every horizon between 1 and 10 years. The framework also has policy implications suggesting that more immigration is not always beneficial. I thus turn to the question of the appropriate stance of immigration policy if the goal is to maximize its productivity benefits. To this end, I propose, but leave to future work, extending the conceptual framework presented here into a quantitative model.[2] Such a model will be used to estimate how much the US government may relax limits on the flow of immigrants, belonging to various skill groups, in order to exhaust the productivity gains of immigration. I will use the preliminary estimates presented here to validate the model before performing the described counterfactuals. In the remainder of the proposal I discuss the conceptual framework and present my baseline estimates. I interpret these estimates through the lens of the conceptual framework.

To begin, appendix A.1 presents a simple task-based model whereby TFP depends on the allocation of tasks in production between domestic and foreign-born labor.[3] An important conclusion from the framework is that an increase in immigration may lead to a rise or fall in TFP.[4] The intuition is that, as immigration rises, so too does the marginal task assigned to immigrants. When immigrants are more productive than native workers at that marginal task, TFP rises. When they are less productive at the marginal task, TFP falls. This has in it the substantive conclusion that regressions of measured TFP on plausibly exogenous immigration flows can help inform policy makers about the gains from loosening or tightening immigration policy. With the objective of maximizing productivity, if the response of measured TFP to immigration flows is negative, as in Ortega and Peri (2009) and Ortega and Peri (2014b), this suggests that policy may be too loose. If the response is positive, as in Peri (2012) and Ortega and Peri (2014a), then policy may be too tight. That is, these regressions quantify the degree of assignment frictions present in a country's labor markets.

Thus, in order to understand the dynamic effects of immigration on TFP, I implement an empirical framework which estimates these effects using the LPIV estimator. To do so, I study all 50 US states and the District of Columbia from 1994 to 2023. I measure TFP as the residual to (7), estimated by by Nonlinear Least Squares. Appendix B.1 describes that process in greater detail. Since migrants are not randomly assigned to US states, I instrument for migrant flows by constructing a shift-share instrument, described in appendix B.3. Figure 1 displays the results of the described LPIV estimator. As described earlier, a US state which experiences a 1 percentage point increase in its immigrant flow, as a percentage of employment, experiences a persistent increase in measured TFP growth of about 1 percentage point for every horizon between 1 and 10 years.[5] In light of my theoretical framework, this suggests that US immigration policy was too tight from 1994 to 2023.

This finding motivates my proposed quantitative extension of the conceptual framework aimed at understanding how US immigration policy can maximize the productivity benefits of immigration. Incorporating multiple skill groups will allow me to understand the economic consequences of changes in both the size and skill composition of migration flows.[6] Additionally, I plan to incorporate occupational data from O*NET in order to better understand the tasks that migrants and US workers engage in following increased migration. For robustness, I am developing an alternative instrument constructed from granted and denied employer petitions from H-1B visa program.[7]

[1] While Peri (2012) and Ortega and Peri (2014a) find that immigration has positive effects on measured TFP, Ortega and Peri (2009) and Ortega and Peri (2014b) find that immigration can have a negative effect on TFP.

[2] Indeed, the conceptual framework presented here belongs to a family of models which are readily brought to the data in a tractable manner. Models in this family are called "task assignment models" and their quantitative applications are reviewed in (Costinot and Vogel, 2015).

[3] See equation (8).

[4] See appendix A.2

[5] The horizon for $h = 10$ should correspond closely to Peri (2012) who uses Census data at the decadal frequency to estimate the relationship. Indeed, the 90% confidence interval easily incorporates his estimates. The LPIV is an improvement on his estimates in that it is able to estimate the entire impulse response function and thereby shed light on the timing of immigration's effects on TFP.

[6] Indeed, Visa caps and border policy can be seen as varying the skill composition of migrant inflows.

[7] US Citizenship and Immigration services provides this data from 2009 to date. H-1Bs are awarded on a lottery system whenever demand exceeds the congressionally mandated cap, differences in award rates across states should be as good as random after controlling for the number of petitions filed and industry value added shares in the state's gross output.

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Figures

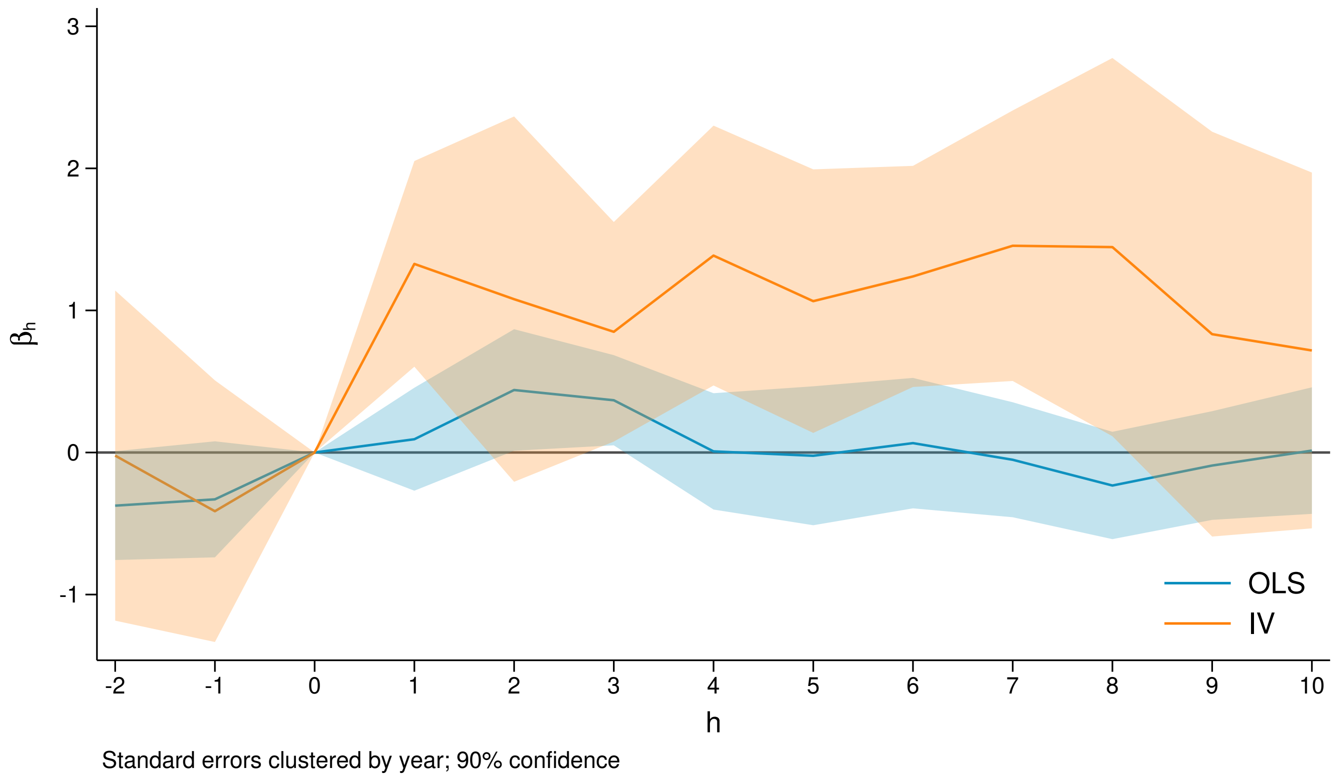

Figure 1: LPIV estimates of the dynamic effects of migration flows on measured TFP growth. Construction of the shift share instrument for the IV estimates is presented in appendix B. The structural specification for this figure is $\hat{z}_{s,t+h} = \phi_s + \eta_t + \beta_h f_{s,t+1} + v_{s,t}$ where $\hat{z}_{t+h}$ denotes the percentage change of measured TFP between t and $t+h$. See appendix B for more detail.

Appendix

A Theoretical Framework

The framework developed here is based on that of Acemoglu and Restrepo (2018, 2019). For expositional purposes I treat capital as exogenous although in the proposed quantitative extension it will be endogenous. The framework is illustrative and, as such, is static. Importantly, while there is no engine of growth in the model, total factor productivity (TFP) is determined endogenously through the assignment of foreign and domestic born labor to various tasks. We will see that technology in this model takes a labor-augmenting form. This is promising for future work since this form of technological growth allows for a characterization of the model through a balanced growth path.

A.1 TFP in a Simple Framework

There is a single final good produced in the economy which is made by combining capital and a continuum of labor services $l(i)$ according to

$$Y = K^{\theta}\left\{\left(\int_0^1 l(i)^{\rho}di\right)^{\frac{1}{\rho}}\right\}^{1-\theta} \qquad \rho\in(0,1), \quad \theta\in(0,1). \tag{1}$$

These labor services are seen as distinct factors of production by the final good producer because each is employed in the completion of a distinct "task", indexed by i. More concretely, the service of eating at a restaurant entails not only the cooking of a meal but the waiting of a table. It is the combination of these tasks that creates the service of eating at one's favorite restaurant.

Each labor service is purchased from perfectly competitive producers at task price $p(i)$. Letting L denote the CES-aggregate of labor services appearing in (1), the first order condition for task i from the final good producer's profit maximization problem yields task demand,

$$l(i) = \left(\frac{1-\theta}{p(i)}\right)^{\frac{1}{1-\rho}}\left(\frac{K}{L}\right)^{\frac{\theta}{1-\rho}}L \tag{2}$$

Tasks are supplied, in turn, by perfectly competitive producers which may combine foreign-born or domestic-born labor according to,[8]

$$l(i) = \alpha^D z^D(i)d(i) + \alpha^F z^F(i)f(i). \tag{3}$$

The quantity $d(i)$ denotes domestic-born labor demanded by intermediate producer of task i and $f(i)$ denotes the quantity of foreign-born labor demanded by task producer i. The values α^D, α^F parameterize the scale of relative differences in the task productivity of either worker type. Importantly, it is assumed that domestic-born labor has comparative advantage in certain tasks,

$$\frac{z^D(i')}{z^F(i')} > \frac{z^D(i)}{z^F(i)} \quad \text{all } i' > i.$$

This suggests that task producers will want to specialize by hiring only one labor type. We will thus look for marginal or 'cutoff'" task I such that

$$\begin{cases} d(i)=0 & \text{and} \quad f(i)>0 \quad \text{for} \quad i<I \\ d(i)>0 & \text{and} \quad f(i)=0 \quad \text{for} \quad i\geq I. \end{cases}$$

We can solve for I by imposing a no-arbitrage condition that requires the unit cost of producer I to be the same when she chooses to specialize using either factor. Solving both of these cost minimization problems and setting their values equal yields the no-arbitrage condition,

$$\frac{w^F}{w^D} = \frac{\alpha^F z^F(I)}{\alpha^D z^D(I)} \tag{4}$$

Furthermore, domestic and foreign-born labor are paid the value of their marginal product so that

$$p(i) = \begin{cases} \frac{w^F}{\alpha^F z^F(i)} & \text{for} \quad i<I \\ \frac{w^D}{\alpha^D z^D(i)} & \text{for} \quad i\geq I. \end{cases} \tag{5}$$

[8] For now I focus on the two factor case with perfect specialization. The later quantitative model will extend this framework to multiple skill groups and make use of extreme value shocks, representing unobserved productive heterogeneity, which induces partial specialization.

Plugging (5) into (2) yields

$$l(i) = \begin{cases} \left(\frac{(1-\theta)\alpha^F z^F(i)}{w^F}\right)^{\frac{1}{1-\rho}} \left(\frac{K}{L}\right)^{\frac{\alpha}{1-\rho}} L & \text{if} \quad i < I \\ \left(\frac{(1-\theta)\alpha^D z^D(i)}{w^D}\right)^{\frac{1}{1-\rho}} \left(\frac{K}{L}\right)^{\frac{\alpha}{1-\rho}} L & \text{if} \quad i \geq I. \end{cases} \tag{6}$$

Let the supply of foreign and domestic-born labor be denoted by F and D, respectively. We can solve for equilibrium wages by clearing the markets for tasks, domestic and foreign born labor. Plugging these wages into (6) and the resulting expression into (1) yields equilibrium output and TFP

$$Y = K^{\theta}\left(Z(I)\left\{\lambda(I)^{1-\rho}(\alpha^F F)^{\rho} + [1-\lambda(I)]^{1-\rho}(\alpha^D D)^{\rho}\right\}^{\frac{1}{\rho}}\right)^{1-\theta}. \tag{7}$$

where

$$Z(I) = \left(\int_0^I z^F(i)^{\frac{\rho}{1-\rho}}\,di + \int_I^1 z^D(i)^{\frac{\rho}{1-\rho}}\,di\right)^{\frac{1-\rho}{\rho}} \tag{8}$$

$$\lambda(I) = \frac{\int_0^I z^F(i)^{\frac{\rho}{1-\rho}}\,di}{\int_0^I z^F(i)^{\frac{\rho}{1-\rho}}\,di + \int_I^1 z^D(i)^{\frac{\rho}{1-\rho}}\,di} \tag{9}$$

A.2 Marginal Task Productivity and the Response of TFP

Plugging the market-clearing wages into the no arbitrage condition (4), I is implicitly defined by

$$\left(\frac{\alpha^D z^D(I)}{\alpha^F z^F(I)}\right)^{\frac{1}{1-\rho}} = \frac{F}{D}\frac{\int_I^1 z^D(i)^{\frac{\rho}{1-\rho}}\,di}{\int_0^I z^F(i)^{\frac{\rho}{1-\rho}}\,di} \tag{10}$$

When immigration rises, captured by an increase in F, the right side increases. To restore equality, the left side must increase, and given our assumption regarding comparative advantage, I must increase. Indeed, this also causes the ratio of integrals on the right side of the expression to decrease as tasks are reallocated and this too helps restore the no-arbitrage condition. Thus, we have that

$$\frac{dI}{dF} > 0.$$

The above comparative static is useful for establishing immigration's effects on TFP. Differentiating (8) with respect to F yields

$$\frac{dZ}{dF} = \frac{1-\rho}{\rho} Z^{1-\frac{\rho}{1-\rho}}\left(\frac{dI}{dF}\right)\left(z^F(I)^{\frac{\rho}{1-\rho}} - z^D(I)^{\frac{\rho}{1-\rho}}\right).$$

Thus, TFP rises if and only if

$$z^F(I)^{\frac{\rho}{1-\rho}} - z^D(I)^{\frac{\rho}{1-\rho}} > 0 \iff \frac{z^D(I)}{z^F(I)} < 1.$$

B Empirical Framework

I assemble a panel of all 50 US states and the District of Columbia from 1994 to 2023. The data come from various sources. I compute the the number of foreign and domestic born workers, ages 16 and older, using American Community Survey (ACS) from 2000 to 2022. I extract this data from IPUMS (Ruggles et al., 2024). Additionally, I compute the same figures using the same sample definition for the years 1994 through 1999 and 2023 using the Current Population Survey (CPS), retrieved from IPUMS (Flood et al., 2024).[9] These extracts define the sample period, which is 1994 to 2023.[10]

In order to estimate TFP by state, I estimate state capital stocks following Peri (2012). That is, I utilize data on the Fixed Assets by industry at the national level from the Bureau of Economic Analysis (BEA). I apportion these national stocks to industries within states based on the state's value added share in that industry. Value added data by state

[9]The git repo associated with this project contains Jupyter notebook with the code that performs these extracts and generates my analysis sample.

[10]Ideally, I would like to go even further back in time but the CPS before 1994 does collect data on citizenship or place of birth prior to 1994. Further, the earliest ACS sample in IPUMS is 2000. Although, appealing to the need for a longer panel in order to increase estimate precision sounds like a reasonable basis on which to apply for special-sworn status with Wisconsin's Research Data Center (RDC).

also comes from the BEA. The industries that I apportion across are the ones defined by the BEA in their Fixed Assets by industry table. That is I construct estimates for the following 19 industries, in every state and DC, from 1994 to 2023: Agriculture, Forestry, Fishing and Hunting; Mining; Utilities; Construction; Manufacturing; Wholesale Trade; Retail Trade; Transportation and Warehousing; Information; Finance and Insurance; Real Estate and Rental and Leasing; Professional, Scientific, and Technical Services; Management of Companies and Enterprises; Administrative and Waste Management Services; Educational Services; Health Care and Social Assistance; Arts, Entertainment, and Recreation; Accommodation and Food Services; Other Services, except Government. Doing so requires converting SIC codes from 1994 to 1996 to NAICS codes. I rely on the employment-weighted crosswalks provided by Schaller and DeCelles (2021).

B.1 Estimating TFP

The log of output in state s at time t can be written

$$\ln Y_{s,t} = \mathbb{E}[\ln Y_{s,t} | F_{s,t}, D_{s,t}] + u_{s,t}$$

Then, equation (7) suggests that

$$\mathbb{E}[\ln Y_{s,t} | F_{s,t}, D_{s,t}] = \theta \ln K_{s,t} + \frac{1-\theta}{\rho} \ln\Big(\lambda^{1-\rho}(\alpha^F F_{s,t})^\rho + [1-\lambda]^{1-\rho}(\alpha^D D_{s,t})^\rho\Big).$$

I further decompose the error term into

$$u_{s,t} = \delta_s + \gamma_t + e_{s,t}$$

where δ_s is a state fixed effect and γ_t is a time fixed effect. The specification of interest is then

$$\ln Y_{s,t} = \delta_s + \gamma_t + \theta \ln K_{s,t} + \frac{1-\theta}{\rho} \ln\Big(\lambda^{1-\rho}(\alpha^F F_{s,t})^\rho + [1-\lambda]^{1-\rho}(\alpha^D D_{s,t})^\rho\Big) + e_{s,t}. \quad (11)$$

I estimate (11) by Non-Linear least squares, treating Greek letters as parameters. As an estimate of TFP I use

$$\hat{Z}_{s,t} = \delta_s + e_{s,t}$$

B.2 LPIV Specification

Equipped with these TFP estimates, the specification of interest is

$$\hat{z}_{s,t+h} = \phi_s + \eta_t + \beta_h f_{s,t+1} + v_{s,t}, \quad h = 1, 2, \ldots$$

where

$$\hat{z}_{z,t+h} = \frac{\hat{Z}_{s,t+h}}{\hat{Z}_{s,t}} - 1 \quad \text{and} \quad f_{s,t+1} = \frac{F_{s,t+1} - F_{s,t}}{L_{s,t}}.$$

$L_{s,t}$ denotes employment in state s at time t and $F_{s,t}$ denote the number of foreign-born workers in state s at time t. Furthermore, ϕ_s, η_t are state and year fixed effects.

B.3 Shift-Share Instrument

Since migrant location choices correlated with other factors which contribute to a state's total factor productivity I build a shift-share instrument for $f_{s,t+1}$. Let i index various migrant groups (Canada, Mexico, etc) and $g_{i,s,t+1}$ the net growth rate of group i in state s between time t and $t+1$. Then, we can decompose $f_{s,t+1}$ as

$$f_{s,t+1} = \frac{\sum_i F_{i,s,t+1} - \sum_i F_{i,s,t}}{L_{s,t}} = \frac{\sum_i (1+g_{i,s,t+1})F_{i,s,t} - \sum_i F_{i,s,t}}{L_{s,t}} = \sum_i w_{i,s,t} g_{i,s,t+1}$$

where $w_{i,s,t} = F_{i,s,t}/L_{s,t}$. The shift share instrument is then given by

$$x_{s,t} = \sum_i w_{i,s,t-1} G_{i,t+1}$$

where $G_{i,t+1}$ is the national growth rate of immigrant group i between times t and $t+1$. I also use lag immigrant shares of state s employment. $x_{s,t}$ satisfied the relevance condition of a good instrument in that immigrant shares of employment with a geographic area tend to be correlated over time. However, the exclusion restriction is most convincingly satisfied if the forces generating variation in national immigrant flows are exogenous to the factors driving TFP in state s.