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ESSAYS ON THE ECONOMICS OF MIGRATION

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ESSAYS ON THE ECONOMICS OF MIGRATION

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Abstract

This dissertation studies the economic consequences of international migration, with a focus on labor markets, fiscal redistribution and household behavior. Chapter 1 analyzes the labor-market and welfare effects of immigration in a general equilibrium model with search frictions, skill heterogeneity and a rich fiscal structure, calibrated to 17 OECD countries. Chapter 2 examines the fiscal impact of immigration by modeling migration choices and migrant self-selection, combining EU-SILC data with a structural framework to simulate counterfactual immigration policy scenarios. Chapter 3 studies how international migration reshapes labor allocation within migrant-sending households, using a collective household model and quasi-experimental evidence from India. By integrating structural modeling with empirical analysis, this dissertation shows that the economic effects of migration are highly context-dependent and mediated by labor-market institutions, fiscal systems and household responses. The contribution is to highlight the importance of policy design in shaping the costs and *especially* the benefits of international migration.

General Introduction

International migration is one of the most salient economic and political phenomena shaping modern economies. Over recent decades, advanced economies have experienced sustained inflows of foreign-born workers, raising fundamental questions about labor-market outcomes, public finances, and welfare in destination countries. At the same time, international mobility also acts as a key channel of labor reallocation, shaping economic outcomes not only in receiving economies but also within migrant-sending households. Although existing research has provided important insights into each of these dimensions, they are often analyzed separately, making it difficult to assess how labor-market mechanisms, fiscal redistribution and household responses jointly shape the economic consequences of migration.

This dissertation addresses this challenge by studying migration within a unified analytical framework that combines labor-market frictions, fiscal redistribution, and household-level adjustment. Across the three chapters, heterogeneity across skills, institutions, and households, plays a central role in shaping the economic effects of migration. Methodologically, the thesis integrates structural modeling and empirical analysis to quantify the mechanisms through which migration affects wages, employment, public finances and welfare.

The first chapter "*Modeling and Evaluating Immigration's Impact on Wages, Tax and Welfare of European Countries*", a joint work with Giovanni Peri and Michele Battisti, develops a quantitative general equilibrium model to reassess the impact of immigration on native welfare in the presence of labor-market frictions and redistributive taxation. Building on search-and-matching frameworks, the model distinguishes between high and low-skill workers, natives and immigrants, and incorporates endogenous job creation, capital accumulation, and skill-biased productivity. A key innovation is the introduction of skill-specific labor taxes and capital taxation, which allows the analysis to separate the roles of tax progressivity and government size. Calibrated to 17 OECD countries using harmonized micro and macro data for the pre-pandemic period, the model is used to simulate immigration shocks with different skill compositions. The results show that the welfare effects of immigration depend crucially on its skill composition. High-skill immigration generates welfare gains for natives in nearly all countries, while low-skill immigration tends to reduce native welfare in many, though not all, cases. When we simulate the actual skill composition of 2019-2024 inflows, which are skill-intensive in most OECD countries, we find positive welfare effects for natives in 15 of the 17 countries, with a cross-country mean gain of 0.17 percent. Fiscal institutions shape the distribution of these effects across skill groups: tax progressivity governs the fiscal incidence of immigration across skill groups, while the size of government scales the aggregate magnitude of welfare effects. Together, these institutional features account for much of the observed cross-country heterogeneity in the welfare impact of immigration.

The second chapter "*The Fiscal Impact of Immigrants: Immigration Policy and Self-Selection*" examines the fiscal impact of immigration by integrating immigration policy and migrant self-selection within a unified framework. It combines descriptive evidence from EU-SILC data with a structural model of migration choices in which households select destinations based on expected wages, taxes, and access to public and private benefits. This approach allows migration flows to respond endogenously to policy-relevant incentives, rather than treating the skill composition of immigrants as exogenous. A conditional logit model provides empirical discipline on migration costs and preferences, and the resulting estimates are embedded in a general equilibrium framework to conduct counterfactual policy simulations. By linking household location choices to aggregate

fiscal outcomes, the chapter provides a quantitative assessment of how immigration policy translates into distributional and budgetary effects. The analysis shows that immigration policy affects public finances not only through the volume of migrant inflows but also through their skill composition, with important implications for labor-market and overall fiscal balances.

The third chapter "*Household Dynamics and Labor Reallocation within Migrant Sending Households*", a joint work with Gargi Dangwal and Maria Jimena Romero, shifts the perspective to migrant-sending households and examines how migration reshapes intra-household labor allocation in India. Using a collective model of household decision-making and quasi-experimental evidence from CPHS, the chapter studies the consequences of male migration for spouses and other household members. The empirical results document increases in female labor supply, reductions in educational investment among younger members, changes in income sources and losses of productive assets following migration. These patterns closely align with the model's predictions, which emphasize substitution of labor within the household and adjustments in resource allocation in response to household separation. The empirical analysis further shows that these adjustments extend beyond short-run responses to migration shocks. These effects are only partially reversed upon migrant return, suggesting persistent adjustments within households.

Overall, this dissertation contributes to the literature on the economics of migration by integrating labor-market mechanisms, fiscal redistribution and household responses within a coherent analytical framework. By combining structural modeling with empirical evidence, the dissertation shows that the economic effects of migration depend crucially on institutional context, policy design and endogenous responses at both the individual and household levels. A central implication is that migration policies cannot be evaluated independently of labor-market institutions and fiscal systems, nor without accounting for behavioral adjustments within households. By providing a unified perspective on these interactions, the dissertation offers quantitative insights that are relevant for the design of immigration and redistributive policies, understanding the economic effects of migration in both destination and origin contexts.

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Chapter 1

Modeling and Evaluating Immigration's Impact on Wages, Tax and Welfare of European Countries

Joint with Michele Battisti and Giovanni Peri

1.1 Introduction

The classic literature on the economic impact of immigration in host countries focuses largely on its effect on employment and wages, usually analyzed within the framework of a canonical frictionless model. In such a framework, immigrants change the supply of labor ([George J. Borjas, 2014](#)), and native wages and employment respond in competitive markets following changes in marginal productivity ([Borjas, 2003](#); [Ottaviano and Peri, 2012](#)). More recently, models including labor-market search and frictions ([Chassamboulli and Peri, 2015](#)), monopsony power of firms ([Amior and Manning, 2020](#)) or worker-firm matching ([Orefice and Peri, 2024](#)) have enriched the insight relative to these effects. At the same time, the literature on the fiscal effects of immigration has provided an understanding of the effects of immigrants on taxes and public transfers, mainly using an accounting framework, i.e., imputing the fiscal cost and fiscal contributions of immigrants under a set of assumptions without usually considering labor market and general equilibrium effects. The two types of effects are rarely analyzed together. Even more rarely, the employment, wage, and welfare impacts of immigration on natives are examined across different fiscal regimes.

This is an aspect underexplored in the literature as the progressivity and size of the public tax and transfer system in the receiving country are relevant in determining potential effects of immigration. The redistributive system can attenuate or amplify the impact of immigration, as immigrants can contribute to the payment of transfers and reduce or increase the tax burden of natives. This paper makes progress on these goals by developing, estimating and simulating a model with labor-market frictions, fiscal redistribution, capital and capital taxation, heterogeneous skills and native-immigrant labor, calibrated to match important features of OECD countries in 2019.

The novelty of this paper is to build on the structure and extend the analysis of seminal papers such as [Docquier et al. \(2014a\)](#), [Chassamboulli and Palivos \(2014\)](#), [Battisti et al. \(2018a\)](#) (including the points raised in [Stark and Byra \(2025\)](#)) and [Chassamboulli and Peri \(2020a\)](#) that consider immigration in labor markets with search and frictions, with more and less skilled and potential productivity effect, by adding a richer and more realistic tax and transfer system. The fiscal effect of immigrants and how the fiscal system interacts with the rest of the economy in determining such effects were missing, or extremely simplified, in those models.

Additionally, we update the estimation and steady state calibration to 2015-2019 (pre-pandemic) data using harmonized international sources (OECD, EU-SILC, LFS) as the baseline scenario and extend simulations to the inflows after covid (2019-2024).

The labor market and fiscal consequences of immigration are at the core of any controversy about the effects of immigrants in OECD economies. A common political narrative claims that immigrants displace native workers, reduce their wages, and impose a net fiscal cost on the public sector. These claims implicitly assume strong competition with natives, decreasing returns to the labor markets, as well as (somewhat contradictorily) stronger dependence of immigrants on welfare transfers and public benefits. For most economists, however, immigrants complement native skills (e.g. [Peri and Sparber \(2009\)](#), [Ottaviano and Peri \(2012\)](#), [Dustmann and Frattini \(2014a\)](#)), and therefore increase the productivity and labor-market options of natives without depressing their wages ([Docquier et al., 2014a](#)). Additionally, especially in economies where the population is ageing and the labor force is shrinking (such as many OECD countries currently), immigrants (and especially the high-skilled ones) can represent a significant positive fiscal contribution to the public sector. Still, their effects can be more or less beneficial to natives depending on their skill levels and on the skill composition of immigrants (see [Dustmann and Frattini \(2014a\)](#) and [Allen et al. \(2025\)](#)). Furthermore, migrants' effect may depend on the type of taxation (how progressive it is) and on the public spending (size of the public sector) of the receiving economy (see [Boeri \(2010\)](#)). While reduced-form studies have highlighted that immigration interacts with welfare in several ways, including through the welfare-magnet hypothesis and the political-economy consequences of immigration (see [Alesina et al. 2021](#); [Allen et al. 2025](#)), few structural models help us to think and quantify how taxation and redistribution shape the incidence of immigration shocks on wages and welfare across different groups of workers and different countries.

The key contribution of this paper is to develop a general equilibrium model with labor-market frictions, capital accumulation and public sector to discuss, calibrate and then simulate the wage-, net income- and welfare-effects of immigration. The model has some key features to capture what are commonly considered the most important effects of immigration in an economy. First, the model features labor markets that employ two types of skills (higher and lower), capturing separate markets for college and non-college-educated (as in [Docquier et al. \(2014a\)](#)). This allows us to separate the labor-market effects of workers with different levels of education. Second, firms search for workers and fill vacancies, separately for high- and low-skilled and they can discriminate against immigrants, paying them different salary, which we model as different outside options as in [Chassamboulli and Peri \(2015\)](#). This allows equilibrium unemployment in each labor market and a job-creation effect from immigrants as firms can extract more surplus from them. Third, the intensity of highly skilled workers in the economy affects aggregate productivity through positive spillovers and technological adoption (as in [Acemoglu and Angrist \(2000\)](#); [Moretti \(2004\)](#); [Docquier et al. \(2014a\)](#)). This generates a positive productivity effect of high-skill-intensive immigration. Finally, we allow physical capital adjustment to maintain a constant rate of return to capital, also allowing immigrants to own physical capital in proportion to their share of labor in the economy. This describes the private sector.

The more innovative part of the model is that it includes a government sector, which redistributes income through differential tax rates and transfers, raises revenues through labor income and capital taxation and provides a pure public good. This richer fiscal and public sector environment can be used to capture the different degree of progressive taxation existing in different OECD countries, the different size of the public good provided (relative to GDP) and ask whether these differences across countries have implications for

the impact of immigrants that were absent in search-based models of immigration such as Battisti et al. (2018a); Chassamboulli and Peri (2015); Chassamboulli and Liu (2024b).

We calibrate our model to 17 different OECD economies in Europe plus the United States using 2015-2019 data (pre-pandemic period), as our baseline. The calibration targets include observed wage gaps, unemployment rates by education and migration groups, fiscal revenues and capital shares. We then use different immigration scenarios to simulate a series of comparative-statics exercises: we analyze how a skill-neutral, a high-skill-intensive and a low-skill-intensive inflow of immigrants equal to 1% of the labor force affect wages and welfare of natives in each of the considered OECD countries. Additionally we simulate the effect of a 1% inflow with the actual skill composition observed in the post-covid years (2019-2024) in those OECD economies.

Several insights emerge from the analysis. First, in all the simulations of the high-skilled-intensive immigration scenario, with immigrants more concentrated among high-skilled workers, we find positive effects on average wages and welfare of natives. In most cases, this scenario produces a positive effect on wages and welfare of both high- and less-skilled natives. This is mainly due to three channels: the productivity impact of high-skilled immigrants, which benefits all natives; a job-creation effect produced by immigrants on local firms that expand vacancies to capture the extra surplus created by immigrants and the contribution of skilled immigrants to financing government transfers (progressive) and the public good.

Second, an important determinant of native welfare and wage gains in response to immigration is the pre-existing wage gap between natives and immigrants. A larger positive gap raises firms' incentives to post vacancies when immigrant labor supply increases, as immigrants generate additional surplus for them. Part of this surplus is translated into job creation, as long as there is free-entry in the posting of new vacancies, which increases labor demand and expands employment opportunities for natives putting upward pressure on their wages. Through firms' vacancy-posting behavior, the surplus generated by immigrant inflows is thus partially redistributed to native workers in the form of higher wages and welfare. A key characteristic that generates this gain for native workers is free entry in the vacancy market, which we assume prevails in the long run in the considered countries¹.

A third result from our analysis is that more redistributive fiscal systems, characterized by larger tax rate gap between high-skilled and low-skilled workers, amplify the positive welfare effects of high-skilled immigration, particularly for high-skilled natives. At the same time, they reduce the welfare gains from low-skilled immigration, especially for low-skilled natives. Stronger redistribution shifts a larger share of government financing toward high-skilled immigrants when inflows are skill-biased, reducing the burden on natives and increasing native welfare. In contrast, when immigration is concentrated among low-skilled workers, redistributive systems place a greater transfer burden on natives, lowering their welfare. There is also a positive benefit from immigrants due to their contribution to financing "pure public good" expenses of the government, but given that those expenses (mainly military spending and debt servicing) are a small fraction of total public spending in most countries, that effect is usually small.

Another feature of our heterogeneity analysis is that country-level results reveal broadly similar welfare responses, consistent with close to 0 average effects on welfare for the "skill-neutral" immigration scenario and significantly positive welfare effects for the high-skilled

¹A substantial degree of monopsony and limitation of entry could stifle this channel. This is what is argued in models such as Amior and Manning (2020), where monopsonistic firms appropriate most of the surplus from immigrants. That situation can prevail in a local market, but in the aggregate economies and over time, we consider free vacancy posting as a more reasonable assumption.

immigration one, but with a few exceptions. The first are Italy, Spain, and Greece, which show a significantly positive welfare effect from skill-neutral immigration. These are largely driven by the job-creation effect of immigrants who exhibit a significant wage gap with natives and benefits labor market with higher unemployment level than elsewhere. The second is the United States, which stands out for smaller positive welfare effects from high-skilled immigration and smaller negative welfare effects from less-skilled immigration. This reflects small native-immigrant wage differentials (in fact slightly reversed for high-skilled, where immigrants earn about 6% more than natives) and low initial unemployment rates, both of which limit the job-creation effect, as well as the small size of the public sector and redistribution.

Finally, and perhaps most importantly, when we move beyond hypothetical scenarios and simulate the effects of a 1 percent flow with the actually observed skill composition of immigrants in 2019–2024 (which we construct using EU-LFS, UK Labour Force Survey, and IPUMS-USA microdata on recent arrivals) we find positive welfare effects for natives in nearly all countries, with a cross-country mean gain of 0.17 percent, high-skilled natives benefitting by 0.07 percent and low-skilled natives experiencing a 0.24 percent rise in welfare. This result derives from the fact that most of the countries considered experienced skill-intensive immigration flows in the 2019–2024 period. Additionally, a welfare decomposition reveals that the channels through which these gains materialize differ between skill groups. Low-skilled natives benefit mainly through pre-tax labor income and capital income, reflecting productivity complementarities and job creation effects, while high-skilled natives gain primarily through savings in the labor tax channel, as incoming skilled immigrants share the fiscal burden of redistribution. Cross-country heterogeneity remains large, with the United Kingdom experiencing the largest gains at +0.5% increase in average welfare and Luxembourg closely following at +0.4%, both benefiting from the very high skill intensity of their immigrants; all other countries experience positive average effects, with the exception of Belgium (-0.01%) and Slovenia (-0.11%), the latter a clear outlier driven by the very low skill intensity of its immigration flows.

This paper contributes to the theoretical and quantitative literature on the economic effects of immigration in two main ways. First, it can estimate total welfare effects by analyzing the combined impact on labor-market outcomes (wage and unemployment) within a framework that incorporates search frictions, wage bargaining, endogenous job creation and productivity effects. Second, it calculates the effects on welfare of natives through the fiscal channel that incorporates labor income taxation, capital taxation, welfare redistribution and public good provisions. Both contributions, and the simulation using post-2019 data, are a substantial novelty relative to existing related models, such as Battisti et al. (2018a), Docquier et al. (2014b) and Chassamboulli and Liu (2024b).

The classical literature analyzing labor-market effects of immigration framed the question in perfect competition and emphasized skill composition and substitution patterns, with mixed evidence on wage impacts across education–experience groups, e.g. Borjas (2003); Card (2009); Ottaviano and Peri (2012). Subsequent contributions introduced richer general equilibrium mechanisms, firm and workers’ heterogeneity (Peri, 2016; Monras, 2020) and capital adjustment (Ottaviano and Peri, 2012). Most of these classical studies abstracted from unemployment, search frictions and the redistributive structure of the fiscal system. In later developments, these models allow for adjustment through task specialization, with natives reallocating toward communication-intensive tasks in response to immigrant inflows. This mechanism attenuates wage effects despite substantial changes in workforce composition (Peri and Sparber, 2009; Foged and Peri, 2016).

More recently, in order to account for unemployment, labor-market frictions and immigrant-natives differentials, a growing literature embedded immigration into search-

and-matching frameworks. Early contributions such as [Chassamboulli and Peri \(2015, 2020a\)](#) developed tractable two-skill models in which immigrants and natives compete for vacancies under Nash bargaining, allowing for both productivity and search heterogeneity. Building on this tradition, [Battisti et al. \(2018a\)](#)², the most direct precursor to this paper, proposes a multi-country quantitative framework that combines search frictions with fiscal redistribution to assess the welfare consequences of immigration. Their calibration across OECD economies linked cross-country differences in unemployment, tax rates, and transfers to the heterogeneous effects of immigration shocks on native workers. This framework provided the first systematic attempt to quantify how labor-market institutions and fiscal redistribution jointly mediate migration’s welfare impact. However, the fiscal side of the economy was highly stylized: it relied on a single tax rate for all workers, lacked a progressive structure, and offered only a partial treatment of capital income with no capital taxation. [Battisti et al. \(2018a\)](#) used data covering 2005-2009, and some refinements to its calibration have been suggested in a recent comment ([Stark and Byra, 2025](#)). This paper expands the fiscal structure, introduces progressive taxation and capital taxation, reconciles the modeling of the productivity effect of high-skilled immigration with the recent literature (e.g., [Docquier et al. 2014b](#)), and updates the period of analysis and our understanding of the interactions between immigration, the public sector, and fiscal redistribution.

The second strand of literature to which this paper contributes examines the fiscal effects of immigration, with a particular focus on how features of the fiscal system shape the wage and welfare impacts of immigrant inflows and the differential effects on high- and low-educated workers. This literature (e.g. [Storesletten \(2003\)](#)), building on a public-finance perspective shows that the net fiscal contribution of immigrants depends on education, employment and earnings profiles, establishing composition as a first-order determinant of immigration’s fiscal impact in welfare states. Using detailed administrative and survey data for the United Kingdom, [Dustmann and Frattini \(2014a\)](#) document large heterogeneity in net fiscal contributions across immigrant groups, highlighting the role of differential tax payments, benefit take-up and eligibility rules. Two recent contributions develop further the interaction of immigrants’ characteristics and fiscal structure in determining their effects. [Ikhenaoe \(2024\)](#) introduces age-based transfers and allows for endogenous skill acquisition by immigrants within a structurally similar environment, highlighting how demographic composition and human capital adjustment interact with redistribution. [Chassamboulli and Liu \(2024a\)](#) calibrate a closely related model that distinguishes between legal and illegal immigration, showing how heterogeneity in tax compliance and benefit eligibility shape fiscal balances and welfare outcomes.

Recent papers introduce additional dimensions to the relation between immigration and fiscal redistribution. [Docquier and Iftikhar \(2019\)](#) analyze the effect of immigrants in countries with large informal sectors and search frictions, focusing on the effect of immigrants on formal–informal wage gaps that affect who gains or loses in these economies. [Ferey et al. \(2023\)](#) studies the potential role of globalization forces (including migration) into the problem of setting up optimal redistribution systems, showing how rising openness can potentially rationalize less redistributive tax systems. Moreover, [Colas and Sachs \(2024a\)](#) investigates the indirect (GE) public finance effects of lower-skilled immigration, delivering very insightful findings while abstracting from search and matching frictions. [Chassamboulli and Liu \(2024b\)](#) develop a model distinguishing between legal and illegal immigrants and embedding a detailed fiscal system with income, payroll, consumption taxes, unemployment insurance and transfers. Their calibration to the U.S. economy (2000–2010) quantifies how differences in legal status alter both job-creation incentives

²Complemented by the note ([Stark and Byra, 2025](#))

and fiscal balance: while illegal immigrants boost employment and output by lowering labor costs, their limited tax payments create a modest net fiscal burden, whereas legal immigrants contribute more fiscally but may reduce job creation. Introducing an informal sector and undocumented immigrants is an important extension, particularly when analyzing immigration in developing countries. Given our focus on OECD economies, these features are less central. We therefore abstract from them and instead emphasize a realistic modeling of progressive fiscal systems. In contrast to this literature, we quantify the fiscal-savings effect of the 2019-2024 inflow of immigrants on OECD countries. We show that, despite immigrants receiving lower wages than natives, immigration contributed substantially to lowering the tax burden for natives, especially the high-skilled, more than compensating this group for the competition in the labor market, while also raising the wages of low-educated workers.

In addition, our paper relates to multi-country models with explicit labor and fiscal linkages, some of which also incorporate international trade, that study the aggregate and distributional effects of immigration. Some of these models incorporate a trade channel that generates market size and composition effects (Aubry et al., 2016), whereas our framework focuses on standard closed-economy mechanisms. Biavaschi et al. (2020) studies the role of human capital externalities, remittances, and trade. Busch et al. (2020) emphasizes potentially negative effects on less educated natives once general equilibrium feedbacks are taken into account. Kancs and Lecca (2018b) show that the long-run economic and fiscal effects of immigration become more favorable when labor-market absorption is faster. All these contributions share with our paper a multi-country general-equilibrium approach.

Lastly, recent studies emphasize the political economy relationship between immigration and fiscal systems. Alesina et al. (2023) show that beliefs about immigrants' fiscal costs reduce support for immigration in more redistributive countries, establishing a direct link between perceived fiscal incidence and political attitudes. Immigration can also reshape electoral coalitions, often increasing support for far-right parties, which points to a feedback loop between perceived fiscal or labor-market pressures and policy preferences (Edo et al., 2019).

Taken together, these contributions motivate our focus on skill-specific taxation, which allows us to evaluate the fiscal impact of immigrants and disentangle the roles of tax progressivity and government size, within a model that incorporates capital and capital taxation and is calibrated to recent data. In our framework, the effects of immigration depend not only on production complementarities, productivity, and matching frictions, but also on both the size and the redistributive structure of the tax and transfer system.

The remainder of the paper is organized as follows. Section 2 documents empirical regularities on immigration, labor markets and fiscal redistribution across the OECD countries in our sample. Section 3 presents the model and characterizes the equilibrium. Section 4 calibrates the model and reports the main results from simulations of immigration inflows with high-skill, neutral, or low-skill concentration. Section 5 presents welfare effects using observed 2019-2024 flows. Section 6 concludes.

1.2 Stylized facts and Trends on Immigration, Labor Markets and Fiscal variables

Our analysis considers European Countries plus the US, the two high-income areas of the world receiving the largest share of world migrants. In this section we provide a compact quantitative picture of those economies in the period 2015-2019 (pre-COVID) which we consider as our starting equilibrium. Then we simulate the impact of migration

flows in the 2019-2024 period, which we will describe in section 1.5, an interesting period experiencing a resurgence of migration in some areas (such as the US, Spain, and the UK) and the most recent data period available to research.

We first describe the composition of the population of the receiving economies into immigrants and natives, separating between tertiary and non-tertiary educated individuals who represent the "High-Skilled" and "Low-Skilled" in the analysis. We then describe important labor market and fiscal variables, which will play an important role in determining the effects of immigration on the receiving economies. We characterize their differences across countries. The analysis draws on harmonized international microdata (European Labor Force Survey, EU-SILC for European Countries, and the U.S. American Community Survey), macroeconomic indicators from the World Bank World Development Indicators and the Penn World Tables, and tax-benefit information from OECD sources (OECD, 2020) and the Luxembourg Income Study, for comparability, which provide skill-specific effective labor tax rates for high- and low-skilled workers.

1.2.1 Immigrant Populations: size and skill composition

Using the EU Labour Force Survey (LFS) and the EU Statistics on Income and Living Conditions (EU-SILC) microdata for the 2015-2019 period, we measure the share of immigrants in total population and their skill distribution relative to natives. Skills are classified according to educational attainment, distinguishing, as mentioned, workers with tertiary education (high-skilled) from those with less education (low-skilled).

Table 1.1: Summary statistics of moments of interest.

Variable	Average	75th PCTL	25th PCTL	Highest (country)	Lowest (country)
[1] Share of immigrants in the population	16.3%	18.9%	9.7%	45.8% (LU)	8.0% (EL)
[2] High-skilled share among immigrants	32.1%	41.0%	25.4%	47.3% (UK)	12.2% (IT)
[3] Immigrant/Native high skill wage gap	0.913	1.039	0.831	1.065 (US)	0.675 (IT)
[4] Immigrant/Native low skill wage gap	0.866	0.966	0.790	1.023 (PT)	0.650 (LU)
[5] Immigrant/Native unemployment ratio (skill-weighted average)	1.755	2.266	1.299	3.396 (SE)	0.795 (US)
[6] Replacement rate	43.5%	52.7%	36.5%	66.8% (BE)	10.0% (EL)
[7] Government share	18.8%	21.8%	17.5%	26.1% (SE)	7.8% (CH)
[8] Capital share	41.0%	44.5%	38.1%	48.1% (IT)	31.3% (CH)
[9] Public good share	8.0%	11.3%	4.9%	20.7% (US)	2.1% (LU)
[10] Labor tax rate, low skill	23.0%	27.7%	21.1%	34.4% (DE)	10.8% (EE)
[11] Labor tax rate, high skill	34.7%	38.6%	29.5%	47.4% (BE)	21.3% (EE)
[12] High/Low tax ratio	1.545	1.633	1.375	1.972 (EE)	1.257 (SI)

Notes: Shares and tax rates shown in percent; ratios are unitless. Sources: EU-SILC, EU-LFS, OECD Taxing Wages, World Bank, and Penn World Table (see Appendix).

Table 1.1 reports the summary statistics and the distribution of key measures relative to immigrants, labor markets, and fiscal and government spending variables across the seventeen countries in our sample. Immigrants represented on average 16.3 percent of the working-age population in the considered countries, ranging from a high of 45.8% in Luxembourg, a very small country relying on immigration in most of its sectors, to a low of 8% in Greece. One fourth of the considered countries has a share of immigrants larger than 19 percentage points. The share of high-skilled among immigrants is also varying significantly across countries. It exceeds 40 percent in several Northern European countries, the UK, Netherlands, Luxembourg and Switzerland, while it is below 30 percent in Southern European economies as well as France and Germany. In many cases, however, immigrants have a larger share of tertiary educated individuals relative to natives, and this is true especially for the recent inflows (as we will see in section 1.5). Such cross-

country variation in skill-intensity of immigrants and their interaction with productivity effects, labor-market frictions and the progressive nature of the fiscal systems, will be at the core of the heterogeneity of our results.

1.2.2 Wage Differentials and Labor-Market Performance

To measure the labor-market performance of natives and immigrants we use EU-SILC data and compute wage ratios between immigrants and natives. In Table 1.1, on average, high-skilled immigrants earn about 90 percent of the comparable natives' wages, while low-skilled immigrants earn around 86 percent of their native counterparts' wages³. In this dimension cross-country heterogeneity is significant and will be consequential when analyzing the effects of immigrants: in the US such gap is close to 0, so that immigrants are similar to natives in their surplus-generating role for firms. To the contrary in Italy, Spain, and Greece, high- and low-skilled immigrants earn as little as 65–70 percent of wages of their native-born counterparts, and this generate a strong job-creation effect, as companies appropriate a large part of the surplus created by them. These differences likely reflect institutional features that affect the relative bargaining power of immigrants, the mobility and sorting of migrants across sectors and occupations as well as the selection of migrants with respect to productivity across countries.

Unemployment patterns and their gap between immigrants and natives also vary substantially across countries. Based on LFS data, the cross-country average ratio of immigrant to native unemployment is 1.75, exceeding one in most European countries and reaching its largest values in Sweden and other northern European countries. The US is an exception in this case too, with lower unemployment ratio between immigrants and natives (ratio 0.79). These gaps are consistent with immigrants facing higher separation rates than natives (a feature that we will model in the analysis), reinforcing the role of labor-market frictions in shaping employment effects of immigrants. Immigrants with lower bargaining power than natives, similar productivity, and higher separation rates would be consistent with conditions promoting the job-creating effect of immigrants, as firms aim to appropriate the surplus they generate by matching with these workers.

1.2.3 Fiscal Structure and Public Spending

Cross-country heterogeneity in fiscal variables plays a central role in how immigration interacts with redistribution, tax burden and public finances. From Eurostat and the U.S. Bureau of Census, we obtain the unemployment benefit replacement rate, which averages 43.5 percent across countries in the sample. It is highest in Belgium and Austria, where replacement ratios exceed 60 percent, and lowest in US, Greece and Portugal, where they are less than 30 percent. Relative to previous studies, such as Battisti et al. (2018a), replacement rates and fiscal indicators are measured using updated and more detailed and harmonized sources, improving cross-country comparability.

To capture the broader fiscal environment, we include data from macro indicators from the World Bank and the Penn World Tables (PWT). As shown in line [7] of Table 1.1 the central government sector spending as share of GDP varies substantially from 8 percent in Switzerland to 26 percent in Sweden, highlighting differences in the scale of public spending in goods and services by the central government. Within the government

³This differential will play an important role in our analysis. The part of this differential driven by lower bargaining power and worse outside options for immigrants relative to natives, generates a higher surplus for firms per worker hired. In competitive markets, this produces a job-creation effect and stronger labor demand as the share of immigrants increases.

spending we measure (and separate) the share of spending in pure public-goods (World Bank), which measures the fraction of government spending devoted to non-rival goods (mainly military spending and Debt servicing). As reported in line [9] of Table 1.1, the public good share of government spending ranges from 2 percent in Luxembourg to 21 percent in the US, where military expenses are an important part of the government. An additional important measure across the economies, linked to the structure of their production, is the capital share, defined as one minus the labor compensation share, capturing compensation to capital (structures, equipment, buildings), accruing to capital-owners of the country. As shown in line [8] of Table 1.1, capital shares vary from 31 percent in Switzerland to 48 percent in Italy, mainly due to the relative importance and capital intensity of different sectors across those countries.

1.2.4 Taxation of Labor and Capital

A key innovation of this study, relative to other analyses of the impact of immigration, is the explicit incorporation of skill-specific labor taxes and of capital taxation, on top of labor income taxation. Using the OECD "Taxing Wages" database, we compute effective labor income tax rates for low- and high-skill workers. Rows [10] and [11] of Table 1.1 show the extent of cross-country variation in these measures: high-skill effective tax rates range from 21 percent in Estonia to 47 percent in Belgium, while low-skill rates are considerably lower, but still as differentiated across countries, from around 11 percent in Estonia to about 34 percent in Germany. The implied high- to low-skill tax ratio averages 1.55, indicating that high-skilled workers face on average a tax burden about 55 percent larger than that of low-skilled workers. Such a significant and heterogeneous degree of progressive labor taxation across European countries suggests that the immigrant population will contribute more or less to the fiscal balance of a government, not only as a function of its size but also of its skill-intensity and the degree of tax progressivity in the country. This fact provides direct motivation for introducing differentiated labor taxes in the model characterizing the fiscal contribution of immigrants, as it depends on the progressivity of taxes and the size of government spending. Access to updated OECD resources, as documented in OECD (2020), allows us to measure effective labor tax wedges with greater precision than most previous studies. Additionally, we include capital taxation in the analysis, with rates from the OECD Corporate Tax Statistics (OECD, 2025). Cross-country data on capital taxation are also available. However, as their measure is sensitive to different classifications and we care more about identifying whether the existence of such taxation affects the impact of immigrants, rather than its specific interactions with country-tax rates, we consider a common rate of 11 percent, derived as the average across the sample countries. Including both skill- and capital-specific tax wedges enables the model to capture how fiscal policy differentially affects workers of different skills and firms, and ultimately individual welfare.

1.2.5 Correlations and Cross-Sectional Variations

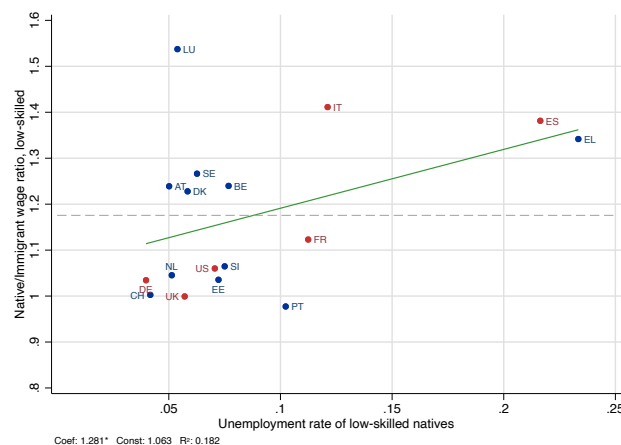
Having identified a set of labor market and fiscal variables that will be important in affecting the impact of immigration on wages, net income and welfare of citizens, we show in this section their variation and correlations across countries, using the average values of these variables in 2015-2019, the initial equilibrium for the analysis.

Figures 1.1 and 1.2 plot the native-to-immigrant wage ratio on the vertical axis against the unemployment rate of natives, for low-skilled and high-skilled workers, respectively. A few interesting features are shown by these charts and are worth noting. First, we

see a positive but modest correlation between the natives' unemployment rate and the native/immigrant wage ratio: countries with higher native unemployment rates also tend to exhibit larger wage gaps between natives and immigrants, and this is true in the high and low-skilled labor markets. Additionally, the identity of countries in the top-right area of the charts and in the bottom-left is similar in the two markets: Italy, Spain, and Greece exhibit high unemployment and high native/immigrant wage ratios, while the US, UK, and to some extent Germany show low values of both. Luxembourg is a notable outlier in the low-skilled market: it combines a very large wage gap with very low native unemployment.

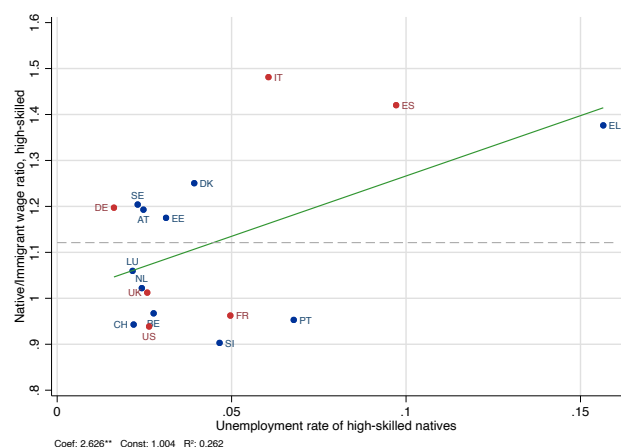
This pattern suggests higher structural frictions in the labor markets of those Mediterranean countries while at the same time low bargaining power of immigrants. Both features are consistent with more rigid labor-market dynamics and protection of insiders in those countries, which enhance the labor-market impact of immigrants. The reason is that when natives face high unemployment driven by low job creation, immigrants, by enhancing firms' surplus and stimulating vacancy posting, can benefit native workers as well.

Figure 1.1: Wage Gaps and Native Unemployment – Lower Education



Notes: The figure plots the native-to-immigrant wage ratio for low-skilled workers (vertical axis) against the unemployment rate of low-skilled natives (horizontal axis) across countries. The solid line shows the fitted linear relationship; the dashed horizontal line indicates the cross-country mean wage ratio. Red markers denote the six largest countries (DE, ES, FR, IT, UK, US); blue markers denote the remaining countries. Data are averages over the 2015–2019 period. Sources: EU-SILC, IPUMS, EU-LFS.

Figure 1.2: Wage Gaps and Native Unemployment – Higher Education

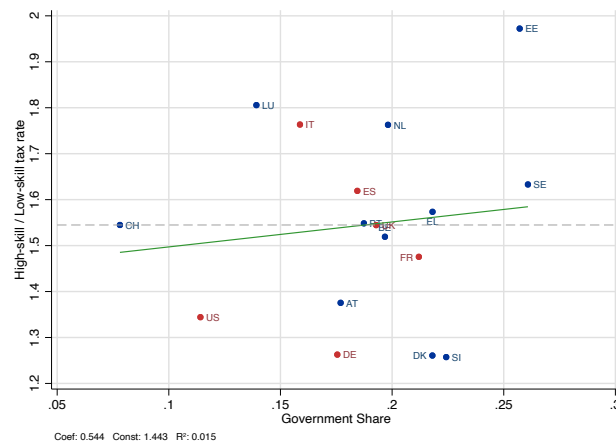


Notes: The figure plots the native-to-immigrant wage ratio for high-skilled workers (vertical axis) against the unemployment rate of high-skilled natives (horizontal axis) across countries. More details in Figure 1.1.

Figure 1.3 plots government size as share of GDP against the tax ratio of high-skilled

relative to low-skilled workers, as a measure of tax progressivity. The correlation between the two measures is very weak, indicating that countries with larger governments do not necessarily operate more progressive tax systems and vice versa. The only countries clearly in the top-right and bottom left are Estonia, with large government and strong progressivity and the US, with low values in both. The other countries show combinations of different features. This implies that we can analyze the simulated impact of immigration using our model and separate its variation across countries with different intensities of tax redistribution and different government sizes.

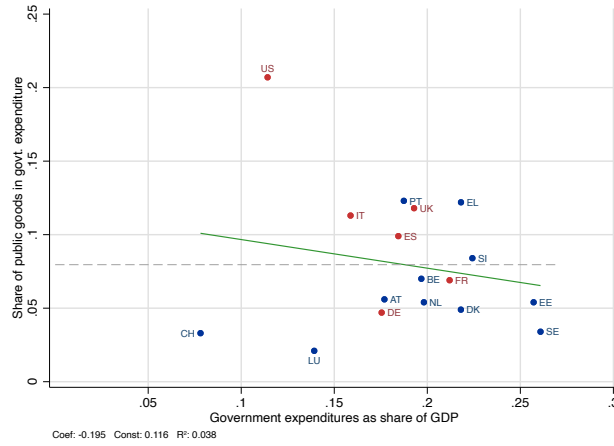
Figure 1.3: Government Size and Tax Progressivity



Notes: This figure plots tax progressivity, measured as the ratio of high- to low-skill effective labor tax rates (vertical axis), against government size, measured by government expenditures as a share of GDP (horizontal axis), across countries. More details in Figure 1.1.

Finally figure 1.4 plots the share of "pure" public goods in government expenditure (mainly defense and public debt servicing) against the government size as share of GDP. The relationship is weakly negative, suggesting that in countries with smaller governments, a larger fraction of their budget is devoted to non-rival, non-excludable public goods. This implies that the larger size of government is driven, in an accounting sense, by the size of welfare spending and transfers, and not by pure public good provision. The United States stands out with a small government size and the highest public good share, reflecting its tradition of a small welfare state, and high defense spending. Nordic countries such as Sweden and Denmark combine large public sectors with relatively low public-good shares, reflecting their emphasis on transfers and individually-targeted benefits. Pure public goods are one channel through which immigrants can generate positive fiscal spillovers for natives: additional contributors share the cost of provision without diminishing its supply. This chart identifies which countries stand to benefit most from this "public-good-funding" channel.

Figure 1.4: Public Good Share and Government Size



Notes: This figure plots the share of pure public goods in total government expenditure (vertical axis) against government size, measured by government expenditures as a share of GDP (horizontal axis), across countries. More details in Figure 1.1.

1.3 Theoretical Framework

The framework of our analysis builds on a series of papers, notably [Chassamboulli and Peri \(2015\)](#); [Chassamboulli and Liu \(2024b\)](#) and [Battisti et al. \(2018a\)](#), which have captured the impact of immigration on labor markets by modeling them within an equilibrium search-and-matching framework with two types of skills (high and low), and borrowing complementarity between those two groups from classic labor models (such as [Autor et al. \(2020\)](#)) and the productivity effect of college educated (high-skill spillovers) from [Moretti \(2004\)](#) and [Docquier et al. \(2014b\)](#). The more novel part of this model is to incorporate skill-specific labor taxation, to capture progressivity of tax rates, capital accumulation and capital taxation to capture the interactions of workers and capital productivity. Additionally, on the public sector side the government provides transfers (unemployment subsidies and redistributive transfers) as well as pure public good (e.g. defense, rule of law).

Each country is treated as a small open economy that produces a homogeneous final good using capital and two types of labor, high-skilled (H), those with tertiary level of completed education and low-skilled (L), those with intermediate and lower levels of education. Each type of labor may be supplied by natives (N) and immigrants (I). Labor markets are segmented by education group and, within each segment, natives and immigrants search for jobs, face unemployment risk, and interact with firms that post vacancies. Important features of the labor market are that search frictions generate equilibrium unemployment and wages are determined endogenously through Nash bargaining between firms and workers. The government collects taxes on labor and capital income to finance unemployment benefits and redistributive transfers.

1.3.1 Production

Aggregate production takes place in a representative firm that combines technology, capital and the two types of labor, with higher and lower levels of education⁴ to produce a homogeneous final good. Output is produced according to the following Cobb–Douglas

⁴We use education and skill interchangeably here, but in terms of data these measures are driven by completed education.

production function:

$$Y = AK^\alpha Z^{1-\alpha}, \quad 0 < \alpha < 1, \quad (1.1)$$

where A denotes country-level total factor productivity, K is the aggregate capital stock, and Z is a composite labor input that aggregates the contributions of workers with different skills and is further discussed below.

Productivity-enhancing high-skill–share

The efficiency of production is enhanced by an endogenous technology term, A , that depends positively on the skill-intensity of the economy and therefore incorporates positive human capital spillovers of the type modelled in [Lucas \(1988, 2015\)](#). Specifically we follow [Docquier et al. \(2014a\)](#), and assume that aggregate productivity rises when the high-skilled share increases in the labor force:

$$A = A_0 \exp \left[\eta \cdot \frac{Q_H}{Q_H + Q_L} \right], \quad (1.2)$$

where A_0 is the exogenous portion of TFP that we do not model, Q_H denotes the population with tertiary education and Q_L the population without tertiary education in the labor force. $\eta > 0$ measures the elasticity of technology with respect to the skilled-labor share. In the calibration, we set $\eta = 0.45$, implying that a higher proportion of high-skilled workers, whether native or immigrant, raises the economy’s technological efficiency. This specification captures the idea that economies with a larger share of tertiary-educated labor tend to be more innovative and can adopt technologies more effectively ([Docquier et al., 2014a](#)). The high-skill–augmenting term A therefore acts as a multiplier on productivity, by strengthening the impact of high-skill labor and amplifying the macroeconomic effects of skill-biased immigration.

Composite labor and skill aggregation

The composite labor input Z is a constant-elasticity-of-substitution (CES) aggregate of the lower- and higher-skill intermediate inputs:

$$Z = [xY_L^\rho + (1-x)Y_H^\rho]^{1/\rho}, \quad 0 < \rho < 1, \quad (1.3)$$

where x is a parameter capturing the relative productivity of the low-skill service inputs and $1/(1-\rho)$ is the elasticity of substitution between the two skill types. A lower ρ implies stronger complementarity between high and low-skilled provided labor services. Notice that we do not introduce immigrant-natives complementarities in the production function as done in many papers such as [Ottaviano and Peri \(2012\)](#); [Peri and Sparber \(2009\)](#) and many others. This may reduce the wage benefit of immigration for natives, but allows us to focus on the interaction between immigrants and natives on the search, job-creation side of labor markets and on the productivity effects of high-skilled workers in general.

Each intermediate labor service input Y_i is linear in effective employment and captures as well the effectiveness of skill-specific labor, which can change with type and origin of workers:

$$Y_i = \sum_{j \in \{N, I\}} (1 - u_{ij}) \pi_{ij} Q_{ij}, \quad i \in \{L, H\}, \quad (1.4)$$

where $u_{i,j}$ is the unemployment rate, hence $(1-u_{i,j})Q_{ij}$ measures employment of skill i and origin j , and $\pi_{i,j}$ is the labor-specific productivity, which can in principle vary with skill level and native-foreign origin. In the quantitative analysis we set $\pi_{ij} = 1$ for all groups, since within-group productivity differences are absorbed by the calibrated separation rates s_{ij} and unemployment disutility h_{ij} (see Section 3.2.1).

Factor prices and returns to capital

The representative firm minimizes its total costs by choosing optimal demands for capital and each type of labor, taking wages, tax rates and welfare payments as given. The tax on capital income t_K is a feature rarely included in these models analyzing labor-market effects of immigrants. Its most important effect is to create a wedge between the marginal product of capital and the net return accruing to households. This implies that an immigration-induced expansion of the composite labor input Z raises the marginal product of capital and triggers increased investment for given international interest rate. However, such investment incentive is only a fraction $1 - t_K$ of the marginal product of capital and such taxation dampens the responsiveness of capital accumulation to changes in labor supply. As a result, the amplification of output and wages through the investment channel response is weaker with this type of taxes than it would be without them. The strength of this effect depends on both the capital share α and the magnitude of the tax wedge.

Importantly, we need to make an assumption about the ownership and distribution of capital income between immigrants and natives. Rather than assigning all capital to natives, we assume that all workers, natives and immigrants, low- and high-skilled, own capital in proportion to their wage rate, weighted by their population share. After-tax capital income $rK(1 - t_K)$ is allocated so that the per-capita capital income received by a worker of type (i, j) is $(w_{ij}/\bar{W})rK(1 - t_K)$, where $\bar{W} = \sum_{ij} w_{ij}Q_{ij}$. Equivalently, the total capital income accruing to group (i, j) is proportional to $w_{ij}Q_{ij}$. In steady-state equilibrium, this ownership structure mirrors the cross-group distribution of labor earnings.

Immigration therefore affects not only labor income but capital income as well via its impact on wage bills, making asset ownership an additional channel through which fiscal effects and welfare responses operate. To maintain comparability across countries and focus on the interaction between immigration and labor-market institutions, we fix the capital tax rate at 11%, in line with the OECD Corporate Tax Statistics (OECD, 2025). This simplification abstracts from cross-country heterogeneity in capital taxation while maintaining its role in mitigating the investment response to immigration. As a result, economies with higher capital intensity still experience stronger complementarities between labor and capital, but the fiscal environment remains harmonized across countries. The marginal products of low- and high-skilled labor, which determine their effective prices p_L and p_H are given by the following expressions:

$$p_L = (1 - \alpha)AK^\alpha x Y_L^{\rho-1} [xY_L^\rho + (1 - x)(Y_H)^\rho]^{\frac{1-\alpha-\rho}{\rho}}, \quad (1.5)$$

$$p_H = (1 - \alpha)AK^\alpha (1 - x) Y_H^{\rho-1} [xY_L^\rho + (1 - x)(Y_H)^\rho]^{\frac{1-\alpha-\rho}{\rho}} \quad (1.6)$$

These prices describe how the interactions between labor composition, relative productivity and total factor productivity shape the factor prices and production incentives. Importantly, notice that a higher share of high-skilled workers raises A , increasing both p_H , p_L through productivity effects and it also increases the incentive to accumulate physical capital. Both channels certainly benefit both types of workers. On the other hand, an inflow of low-skilled workers expands Y_L and boosts the productivity of capital and high-skilled labor through complementarity, but reduces the productivity of less skilled ones.

1.3.2 Labor Market Frictions and Matching

Labor markets are modelled as in Chassamboulli and Palivos (2014), which provide the foundations to understand the job-creation effect of immigrants. They are segmented by

level of education, with separate matching processes for low- and high-skilled workers⁵. Within each skill segment, both natives and immigrants search for jobs, face unemployment risk and interact with firms that post vacancies.

Search frictions imply that, at any moment, some workers remain unemployed and look for a job while firms have unfilled vacancies and look for workers.

Job creation follows a standard constant returns-to-scale matching function:

$$M(U_i, V_i) = \xi U_i^\varepsilon V_i^{1-\varepsilon}, \quad i \in \{L, H\}, \quad (1.7)$$

where U_i and V_i denote the number of unemployed workers and vacancies in the skill market; $\xi > 0$ is the matching efficiency and ε measures the elasticity of matches with respect to unemployment. Defining labor-market tightness as $\theta_i = V_i/U_i$, the job finding rate for workers and the vacancy-filling rate for firms are

$$M_i/U_i = m(\theta_i) = \xi \theta_i^{1-\varepsilon}, \quad M_i/V_i = q(\theta_i) = \xi \theta_i^{-\varepsilon} \quad (1.8)$$

Unemployment workers find jobs with probability $m(\theta_i)$, while filled positions are destroyed at rate s_{ij} , which may differ between natives and immigrants. A higher value of $s_{i,I}$ relative to $s_{i,N}$ captures the fact that immigrants are likely more subject to events that end their job duration such as re-migration, return migration and even higher internal mobility.

Bellman Equations

Firms and workers meet through the matching process and negotiate over the surplus generated by a productive match. The value of each state (employment, unemployment or vacancy) is characterized by a system of Bellman equations. These values summarize the discounted flow of payoffs accruing to firms and workers given the arrival and separation rates defined above.

For a firm posting a vacancy of skill type $i \in \{L, H\}$, the flow-value of such a vacancy posting is given by the following expression :

$$rJ_i^V = q(\theta_i) [\varphi_{iN}J_{iN}^F + \varphi_{iI}J_{iI}^F - J_i^V] - c_i, \quad (1.9)$$

where r is the interest rate, c_i is the per-period cost of maintaining a vacancy and $q(\theta_i)$ is the probability of filling a vacancy given labor-market tightness θ_i . The term in brackets represents the expected surplus from a successful match: with probability $\varphi_{i,j}$ the position is filled by a worker of type $j \in N, I$.

Once matched, a filled job yields value J_{ij}^F to the firm, whose expression is as follows:

$$rJ_{ij}^F = \pi_{ij}p_i - w_{ij} - s_{ij} (J_{ij}^F - J_i^V), \quad (1.10)$$

where p_i is the skill-specific price of output, π_{ij} is the efficiency of workers of type i, j , $w_{i,j}$ is the negotiated wage and s_{ij} the exogenous separation rate. Matches are destroyed at rate s_{ij} after which the firm incurs a loss equal to the difference between the value of a filled position and a vacancy. As noted in Section 3.1.2, in the quantitative analysis we set $\pi_{ij} = 1$.

Workers face a symmetric decision problem. The value of employment for a worker of type (i,j) satisfies the following equation:

$$rJ_{ij}^E = g + rk_{ij} + (1 - t_i)w_{ij} - s_{ij} (J_{ij}^E - J_{ij}^U), \quad (1.11)$$

⁵An important phenomenon identified by empirical economists is the "downgrading" of foreign workers, meaning that high-skilled ones can be employed in low-skilled jobs (see e.g' [Dustmann et al. \(2013\)](#)). We do not incorporate this feature in the model. Instead, within-group productivity heterogeneity arises endogenously through the calibrated separation rates s_{ij} and unemployment disutility h_{ij} , which together reproduce observed within-skill native-immigrant wage gaps.

where $t_i \in \{t_L, t_H\}$ is the skill-specific labor-income tax rate, g is the flow value of the per capita public transfer to each individual, and k_{ij} represents the capital income accruing to individuals. The flow-values of capital income and public goods are independent of the individual employment status, hence identical between employed and unemployed workers. In case of job loss, due to a separation, workers give up the surplus $(J_{ij}^E - J_{ij}^U)$.

When individuals are unemployed, they receive monetary benefits from unemployment transfers, b_{ij} . We also allow them to experience a utility-flow component h_{ij} . This term captures the non-monetary effects of unemployment, acknowledging that the welfare consequences of job loss can go beyond financial compensation. The Bellman equation for unemployment is:

$$rJ_{ij}^U = g + rk_{ij} + b_{ij} + h_{ij} + m(\theta_i) (J_{ij}^E - J_{ij}^U). \quad (1.12)$$

For natives we set $h_{iN} = 0$, while for migrants h_{iI} this term might be negative ⁶. It captures the additional stigma and consequences of being unemployed for immigrants including the risk of losing status, the cost of higher isolation, the fastest deterioration of skills. This summarizes the worse outside option of immigrants relative to natives as in [Chassamboulli and Peri \(2015\)](#).

These Bellman equations determine together the value of employment, unemployment and vacancies for each worker-firm pair in the economy. They imply that job creation and wage determination depend not only on productivity and separation rates, but also on the fiscal wedge introduced by labor taxes t_i , the capital share of output and the public good component g . These elements shape together the transition of immigration shocks to labor markets and welfare.

Wage Determination

Wages are determined through Nash bargaining between firms and workers once a match is formed. The bargaining takes place within each skill segment $i \in \{L, H\}$, conditional on the identity of the worker $j \in \{N, I\}$. Firms and workers negotiate over the surplus from employment, taking as given the flow values of employment and unemployment derived above. Since wages are taxed, the firm's surplus is evaluated net of the skill-specific labor tax, which affects the division of the surplus but not the structure of the bargaining problem as in [Stark and Byra \(2025\)](#)⁷. Incorporating this into the Nash bargaining rule yields the equilibrium condition:

$$(1 - \beta) (J_{ij}^E - J_{ij}^U) = \beta(1 - t_i) (J_{ij}^F - J_i^V), \quad (1.13)$$

Combining this condition with the firm's zero-profit condition for vacancy creation ($J_i^V = 0$) yields the steady-state wage expression. Following the extended version of the model, the equilibrium wage for each skill-origin group is:

$$w_{ij} = \beta \frac{r + s_{ij} + \xi \theta_i^{1-\varepsilon}}{r + s_{ij} + \beta \xi \theta_i^{1-\varepsilon}} p_i + (1 - \beta) \frac{(r + s_{ij})(b_{ij} + h_{ij})}{(1 - t_i) [r + s_{ij} + \beta \xi \theta_i^{1-\varepsilon}]}. \quad (1.14)$$

In this setting, differences in fiscal wedges, separation rates, and labor-market tightness translate directly into systematic cross-country variation in wage gaps between natives and immigrants and across skill groups. Relative to [Battisti et al. \(2018a\)](#), the introduction of skill-differentiated labor taxes, together with the adjustment to the bargaining rule, ensures that the wage schedule incorporates the true incidence of taxation on the firm-worker surplus. As a result, the model can map observed heterogeneity in labor market and demographic composition into equally heterogeneous wage responses, providing a more accurate description of cross-country wage differentials.

⁶In the replication code, h_{ij} is stored as a positive magnitude and enters with a minus sign in the Bellman and wage equations. Denoting the code's variable by $\tilde{h}_{ij}$, the equivalence is $h_{ij} = -\tilde{h}_{ij}$.

⁷[Battisti et al. \(2018a\)](#), on the other hand, model this as Kalai bargaining.

1.3.3 Public Sector

The government collects revenue from two sources: labor-income taxes, which differ by skill level (t_L, t_H) and a capital-income tax t_K , calibrated to a common value across countries. Government expenditures consist of unemployment benefits $b_{i,j}$, a per-capita transfer g interpreted as a publicly provided rival good, and a pure public good $\bar{g}$. The government budget constraint is:

$$\sum_i \sum_j b_{ij} U_{ij} + g \sum_i \sum_j Q_{ij} + \bar{g} = t_L \sum_j w_{Lj} E_{Lj} + t_H \sum_j w_{Hj} E_{Hj} + t_K rK. \quad (1.15)$$

The left-hand side represents total spending on unemployment benefits and transfers. The right-hand side aggregates revenue from labor taxes and the capital tax. Because employment, wages, and capital respond to immigration, the tax base is endogenous and fiscal spillovers depend on the structure of the tax system.

The replacement rate $\varrho \equiv b_{ij}/[(1 - t_i)w_{ij}]$ is taken as a country-specific parameter from the OECD Benefits and Wages database, identical across skill and origin groups within each country. Given the equilibrium wages w_{ij} and labor tax t_i , the level of unemployment benefits is then $b_{ij} = \varrho(1 - t_i)w_{ij}$; benefits therefore vary across groups only through the equilibrium net wage. Type-specific unemployment rates u_{ij} , by contrast, are matched in the calibration through the four separation rates s_{ij} (see Section 4.1). The empirical share of total government spending in GDP, $(g \sum_{ij} Q_{ij} + \bar{g})/Y$, is taken from the Penn World Tables, and the share of pure public goods within total government spending, $\bar{g}/(g \sum_{ij} Q_{ij} + \bar{g})$, is taken from the World Bank WDI. These two empirical moments jointly pin down g and $\bar{g}$ at the initial equilibrium. In the counterfactual exercises, g and $\bar{g}$ are held fixed at their calibrated values, while the skill-specific labor taxes t_L and t_H adjust to satisfy the government budget constraint. The capital tax t_K raised on capital income rK is held constant across countries for simplicity. Capital is allocated across skill-origin groups proportionally to their share of the aggregate wage bill, as described in Section 3.1.3.

1.3.4 Equilibrium

For each country, the equilibrium is a vector of endogenous variables that jointly satisfy the labor-market, production, and fiscal conditions of the model.

Endogenous variables. For each skill segment $i \in \{L, H\}$ and origin $j \in \{N, I\}$, the equilibrium determines: labor-market tightness θ_i and unemployment rates u_{ij} ; wages w_{ij} ; skill-specific output prices p_i ; unemployment benefits b_{ij} ; the aggregate capital stock K ; the labor-income tax rates t_L and t_H ; and the per-capita public transfer g . The pure public good $\bar{g}$, the population shares Q_{ij} , the replacement rate ϱ , the capital-income tax t_K , and the tax-progressivity ratio t_H/t_L are taken as country-specific parameters.

Equilibrium conditions. Given these parameters, the endogenous variables jointly satisfy:

- (i) the steady-state unemployment identities $u_{ij} = s_{ij}/[s_{ij} + m(\theta_i)]$, where $m(\theta_i) = \xi \theta_i^{1-\varepsilon}$;
- (ii) the wage equations derived from Nash bargaining (equation (1.13));
- (iii) the free-entry condition for vacancy posting, equation (1.16) below;

- (iv) the marginal-product equations for p_L and p_H , and the no-arbitrage condition equating the after-tax marginal product of capital to its user cost, $(1 - t_K) \text{MPK} = r + \delta$;
- (v) the government budget constraint (3.5), which pins down the tax rate;
- (vi) the benefit rule $b_{ij} = \varrho(1 - t_i)w_{ij}$.

Intuition. The equilibrium is the fixed point at which firms' vacancy-posting decisions, workers' wages, and the public budget are mutually consistent. Free entry links the expected return from a match to its cost, which depends on wages, separation rates, and productivity. Wages are set by Nash bargaining, which interacts with the fiscal wedge through skill-specific labor taxes. The government budget constraint then determines those taxes endogenously, closing the loop between labor-market outcomes and the fiscal environment. Capital adjusts so that its after-tax marginal product equals the common interest rate plus depreciation.

We now formalize the free-entry condition that, together with the wage schedule, pins down labor-market tightness. For each skill-specific labor market $i \in \{L, H\}$, posting a vacancy entails a flow cost c_i and yields an expected return equal to the weighted surplus from hiring a native or an immigrant worker. Let θ_i denote labor-market tightness and $q(\theta_i)$ the probability that a vacancy is filled. Using the value of a filled job for a worker of type $j \in N, I$, the free-entry condition implies that the expected job surplus must satisfy

$$q(\theta_i) \sum_{j \in \{N, I\}} \varphi_{ij} \frac{\pi_{ij} p_i - w_{ij}}{r + s_{ij}} = c_i, \quad (1.16)$$

The introduction of skill-specific income taxes modifies this mechanism directly through wages: given the Nash bargaining, the worker's surplus is reduced by the tax rate t_i and the firm's surplus is correspondingly larger. Consequently, cross-country differences in t_L and t_H , together with observed wage gaps between natives and immigrants, translate into systematic differences in the job-creation response to immigration. An inflow of workers who command relatively low wages, such as low-skill migrants in Southern Europe, raises the firm surplus and expands vacancy posting. Conversely, in economies where immigrant wages are close to those of natives, or where labor-income taxes are high, the same inflow generates a much weaker job-creation response.

Separation rates contribute an additional layer of heterogeneity. When immigrants face higher separation rates than natives, the present value of a match declines, reducing the incentive to create vacancies. Finally, the productivity terms themselves respond endogenously to the skill composition of employment: because high-skill labor enters the composite input through the technology A , immigration that increases the share of high-skill employment raises the marginal product of both firm types and strengthens job creation. Altogether, the job-creation condition summarizes how fiscal wedges, wage differentials, separation rates, and high-skill complementarity jointly determine the cross-country variation in labor-market responses to immigration.

1.4 Quantitative Analysis

1.4.1 Calibration

The model is calibrated using cross-country data for the 2015–2019 period, in order to obtain the initial equilibrium. In Section 1.5 we use data on immigration flows in 2019–2024. To limit the influence of business-cycle fluctuations, we construct moments for labor-market outcomes and migration stocks by averaging over the 2015–2019 period,

while the parameters that are not sensitive to business cycles are pinned down using 2019 data. The calibration draws on micro and macro data from multiple sources, including the EU Statistics on Income and Living Conditions (EU-SILC), the EU Labour Force Survey (EU-LFS), IPUMS for the United States, the Penn World Tables, the World Bank World Development Indicators, the OECD Taxing Wages database and the OECD Corporate Tax Statistics.

Model parameters are chosen to jointly match a set of empirical moments across countries, including unemployment rates (by education group and migration status), native-immigrant wage differentials, the skill composition of natives and migrants, immigrant population shares, as well as key features of national tax-benefit systems, namely the tax ratio for college and non-college-educated, government spending as share of GDP and, within it, the percentage of pure public good. The calibration strategy addresses identification issues highlighted in earlier work by attributing within-group native-immigrant heterogeneity to differences in separation rates s_{ij} and unemployment disutility h_{ij} , jointly calibrated to match observed wage gaps and unemployment rates, following the same procedure as in Chassamboulli and Palivos (2014) and Chassamboulli and Peri (2015). The ratio of high- to low-skilled effective labor tax rates, t_H/t_L , is constructed from administrative and survey-based sources and imposed as a country-specific calibration target (OECD, 2019b); the absolute levels of t_L and t_H are then determined by the government budget constraint. Model parameters fall into two groups. The first group, reported in Table 1.2, is pinned directly from data or the existing literature, and combines parameters that are common across countries (β , ε , ρ , r , δ , η) with parameters that vary at the country level (the replacement rate ϱ , the capital share α , and the four population shares Q_{ij}). The second group consists of eleven country-specific parameters that are jointly calibrated to match the eleven empirical moments described in Table 1.3. Table 1.4 reports the mean and standard deviation of these calibrated values across our 17 countries.

The pure public good $\bar{g}$ is jointly solved alongside g through the two identities $g\text{share} = (g \sum_{ij} Q_{ij} + \bar{g})/Y$ and $\bar{g}/Y = g\text{barshare} \cdot g\text{share}$, and is not reported separately in Table 1.4.

Table 1.2: Parameters taken from available data or the literature.

Parameter	Description	Mean	S.D.	Source
<i>Parameters without country variation</i>				
β	Worker bargaining power	0.5	n.a.	Petrongolo and Pissarides (2001)
ε	Matching elasticity	0.5	n.a.	Petrongolo and Pissarides (2001)
ρ	Parameter governing substitution elasticity	0.5	n.a.	Ottaviano and Peri (2012)
r	Interest rate (monthly)	0.004	n.a.	Chassamboulli and Palivos (2014)
δ	Depreciation rate (monthly)	0.0061	n.a.	Chassamboulli and Palivos (2014)
η	Elasticity of technology w.r.t. skilled-labour share	0.45	n.a.	Docquier et al. (2014)
<i>Parameters varying across countries</i>				
ϱ	Replacement rate	0.39	0.13	OECD Benefits and Wages
α	Capital share	0.35	0.05	Penn World Tables
Q_{LN}	Low-skilled natives	0.692	0.063	Eurostat LFS, IPUMS
Q_{HN}	High-skilled natives	0.308	0.063	Eurostat LFS, IPUMS
Q_{LI}	Low-skilled immigrants	0.138	0.102	Eurostat LFS, IPUMS
Q_{HI}	High-skilled immigrants	0.080	0.099	Eurostat LFS, IPUMS

Notes: We normalize the size of the native labor force to unity: $Q_{LN} + Q_{HN} = 1$

Table 1.3: Matched moments.

Moment	Source	Mean	S.D.
<i>Moments without country variation</i>			
Average job duration, low skilled (months)	Chassamboulli and Palivos (2014)	29.4	n.a.
Average job duration, high skilled (months)	Chassamboulli and Palivos (2014)	52.6	n.a.
<i>Moments varying across countries</i>			
Native wage premium, low skilled	EU-SILC, IPUMS	1.176	.041
Native wage premium, high skilled	EU-SILC, IPUMS	1.121	.044
Skilled-unskilled wage ratio, native workers	EU-SILC, IPUMS	2.148	0.087
Unemployment rate low-skilled natives	EU LFS, IPUMS	0.088	.014
Unemployment rate low-skilled immigrants	EU LFS, IPUMS	0.133	0.017
Unemployment rate high-skilled natives	EU LFS, IPUMS	0.045	0.009
Unemployment rate high-skilled immigrants	EU LFS, IPUMS	0.089	0.014
Government expenditures as % of GDP	Penn World Tables	0.188	0.011
Pure public good spending as % of GDP	World Bank WDI	0.013	0.005
High-/low-skilled tax ratio (t_H/t_L)	OECD Taxing Wages	1.545	0.206
Real per capita GDP, US = 1 (PPP)	World Bank WDI	0.852	0.079

Notes: All shares refer to working age population (aged 17–62) years. For unemployment rates, we use 2015–2019 averages. The moments refer to the average, all moments are constructed for each of our 17 countries.

Table 1.4: Calibrated parameter values.

Parameter	Description	Mean	S.D.
ξ	Match efficiency parameter	0.529	0.230
A	Total factor productivity	0.343	0.106
x	Low-skill share in production of intermediates	0.413	0.046
c_H	Cost of a high-skill vacancy	0.705	0.534
g	Public expenditures (per capita)	0.142	0.049
$\bar{s}_{LN}$	Monthly job separation rate, low-skilled natives	0.030	0.004
$\bar{s}_{LI}$	Monthly job separation rate, low-skilled immigrants	0.051	0.014
$\bar{s}_{HN}$	Monthly job separation rate, high-skilled natives	0.016	0.003
$\bar{s}_{HI}$	Monthly job separation rate, high-skilled immigrants	0.036	0.010
h_{LI}	Unemployment disutility for low-skilled immigrants	0.330	0.595
h_{HI}	Unemployment disutility for high-skilled immigrants	0.189	0.906

Notes: Summary statistics of parameters calibrated on empirical moments for 17 countries. Separation rates exclude remigration rates.

1.4.2 Comparative Statics Results

In order to analyze the effects of immigration, we implement three comparative statics exercises, all of which investigate the effects of a one percentage-point increase in the stock of foreign-born workers. We analyze three scenarios, which differ in the skill composition of these immigrant inflows, but not in their size, fixed at 1% of the labor force of the receiving country. Scenario 1 (“skill neutral”) assumes that immigrants have the same skill composition as non-migrants in the initial steady state. Scenario 2 (“higher-skilled”) considers an inflow that is twice as intensive in high-to-low-skilled workers relative to natives, namely where the share of high-skilled in the net inflow is twice the share of high-skilled in the stock of natives. Scenario 3 (“lower-skilled”) instead assumes an inflow that is twice as intensive in low- and medium-skilled workers relative to the stock of natives. In all cases, the size of the labor force increases by one percentage point because of immigration, while the composition of immigration varies across scenarios. These experiments allow us to analyze how different skill-intensity of immigrants affects the wage, fiscal and welfare effects on natives, and how these effects differ across countries, depending on some of their crucial labor market and fiscal variables characteristics.

We first present the main welfare effects on natives in the scenarios we just described. Table 1.5 shows the welfare effects for natives of a one percentage-point increase in immigration in the six largest countries of our sample (i.e. Germany, Spain, France, Italy, the United Kingdom, and the United States). These countries are very large economies in the developed world and have been recipients of significant inflows of immigrants during the last two decades. Table 1.6 extends the analysis to the full set of countries and reports mean and median effects across destinations. Welfare changes are expressed as percentage variations in steady-state consumption equivalents.

Table 1.5: Welfare effects of a 1pp increase in immigration: main countries scenarios

Country	Welfare measure	Scenario 1	Scenario 2	Scenario 3
Germany	W_N	0.02%	0.18%	-0.10%
	W_{LN}	0.02%	0.28%	-0.18%
	W_{HN}	0.01%	0.01%	0.01%
Spain	W_N	0.19%	0.43%	-0.01%
	W_{LN}	0.16%	0.47%	-0.10%
	W_{HN}	0.22%	0.39%	0.08%
France	W_N	-0.03%	0.12%	-0.15%
	W_{LN}	-0.01%	0.23%	-0.20%
	W_{HN}	-0.06%	-0.04%	-0.08%
Italy	W_N	0.21%	0.37%	0.10%
	W_{LN}	0.19%	0.42%	0.05%
	W_{HN}	0.25%	0.22%	0.28%
United Kingdom	W_N	0.00%	0.19%	-0.15%
	W_{LN}	-0.02%	0.27%	-0.26%
	W_{HN}	0.03%	0.10%	-0.03%
United States	W_N	0.03%	0.06%	0.01%
	W_{LN}	0.10%	0.16%	0.05%
	W_{HN}	-0.03%	-0.03%	-0.02%

Notes: Welfare effects are reported as percentage changes in steady-state consumption equivalents following a one percentage point increase in the stock of immigrants. W_N denotes average native welfare, while W_{LN} and W_{HN} refer to low- and high-skill natives. Scenario 1 assumes neutral skill composition; Scenario 2 (Scenario 3) considers an inflow twice as intensive in high-skilled (low-skilled) workers. In all cases, the labor force increases by one percentage point.

A few findings emerging from Tables 1.5 and 1.6 are worth emphasizing. First, considering the “balanced” (i.e. skill-neutral) Scenario 1, the net inflow of immigrants equal to 1% of the receiving country labor force (which is a significant inflow and comparable to the one experienced in the US in 2022, a high-immigration year, or by Spain in several years between 2000 and 2010) generates a extremely small average effect on the welfare of natives, a few hundredths of a percentage point. These average effects are, in most cases, positive (in five of the six largest economies). Such a balanced inflow in most cases has small to no significant effect on less educated natives’ welfare, which ranges from -0.02% (for France) to +0.19% (for Italy). In some countries, such as Italy and Spain, such a balanced inflow of immigrants has a moderate positive effect on native welfare of both skilled and unskilled. The reason for this positive effect is the strong job-creation and labor-market-tightening effect of immigrants in those countries, where the native-immigrant gap in wages is significant and unemployment is high, before immigration among natives. The difference in immigrants in stimulating firms’ job creation and easing local unemployment is the reason for such positive effects.

Second, across virtually all countries in the sample, Scenario 2 (corresponding to a high-skilled immigration inflow) generates positive and sometimes significant average welfare effects for natives, and such effects are positive for both skilled and unskilled natives. These gains are sizeable and systematically larger than those obtained under

Scenario 1. This pattern is particularly clear in several countries, in which moving from a neutral skill composition of Scenario 1 to a high-skilled inflow of Scenario 2 turns weak or negative welfare effects into consistently positive gains for natives, such as in the case of France, Belgium and Portugal. Spain and Italy continue to experience very significant positive welfare effects, and now the group of low-skilled workers experiences a significant positive welfare effect close to +0.5%. Overall both the average and skill-specific mean and median effects reported in Table 1.6 are positive for Scenario 2.

Finally, Scenario 3, characterized by more intense low-skilled immigration inflow, generates negative welfare effects for natives in most countries. In this case, the expansion of low-skilled labor tends to place downward pressure on wages, reduces productivity and attenuates the positive job creation effects. This type of inflow, additionally increases the fiscal burden associated with redistribution as the newcomers contribute less to the public sector, per person, than natives.

Notable exceptions arise in some countries, where the labor-market stimulus from immigrants (job creation effect) can be stronger and more relevant due to high unemployment. In the case of Italy, for instance, positive welfare effects prevail even in the scenario with more intensive low-skilled inflows. This outcome reflects a combination of large immigrant-native wage gaps, low capital share, high local unemployment and a relatively small size of government. Together, these features strengthen the job-creation and capital-accumulation channels while limiting fiscal burden on natives, allowing low-skilled immigration to translate into net welfare gains for natives. This heterogeneity underscores that the welfare consequences of low-skilled immigration, while not as positive as those of a neutral or high-skilled inflow, depend critically on the interaction between wage differentials, unemployment conditions, capital intensity, and the structure of taxation and redistribution.

An additional consideration is that for the United States, a country with small immigrant-native wage gaps, low unemployment, low tax progressivity and a small government sector, but a significant public good component (military, debt servicing), the effects of migration are rather mitigated, and especially low-skilled natives tend to benefit from immigration, mainly through a lower burden of financing public expenditures on pure public goods.

These results imply that country-specific analysis is needed to understand which country gains the most from immigration and from which channel and for which group these effects are more prevalent. In the next sections, we will systematically associate the simulated effects with characteristics of the receiving countries to develop more clearly our understanding of which structural factors are associated with the impact of immigration on wages and welfare of natives.

Table 1.6: Welfare effects of a 1 pp increase in immigration: cross-country scenarios

Countries	Scenario 1			Scenario 2			Scenario 3		
	W_N	W_{LN}	W_{HN}	W_N	W_{LN}	W_{HN}	W_N	W_{LN}	W_{HN}
Austria	0.04%	0.04%	0.04%	0.20%	0.30%	0.05%	-0.08%	-0.16%	0.03%
Belgium	-0.07%	-0.05%	-0.10%	0.06%	0.19%	-0.08%	-0.18%	-0.24%	-0.12%
Denmark	0.08%	0.07%	0.09%	0.25%	0.33%	0.13%	-0.05%	-0.13%	0.06%
Estonia	0.02%	0.01%	0.04%	0.24%	0.27%	0.19%	-0.16%	-0.21%	-0.08%
France	-0.03%	-0.01%	-0.06%	0.12%	0.23%	-0.04%	-0.15%	-0.20%	-0.08%
Germany	0.02%	0.02%	0.01%	0.18%	0.28%	0.01%	-0.10%	-0.18%	0.01%
Greece	0.13%	0.11%	0.16%	0.37%	0.40%	0.31%	-0.04%	-0.09%	0.05%
Italy	0.21%	0.19%	0.25%	0.37%	0.42%	0.22%	0.10%	0.05%	0.28%
Luxembourg	-0.08%	-0.12%	0.00%	0.10%	0.13%	0.04%	-0.20%	-0.31%	-0.02%
Netherlands	0.00%	0.00%	-0.01%	0.19%	0.28%	0.09%	-0.16%	-0.23%	-0.08%
Portugal	-0.06%	-0.06%	-0.06%	0.11%	0.19%	-0.07%	-0.16%	-0.22%	-0.05%
Slovenia	-0.02%	0.02%	-0.07%	0.11%	0.26%	-0.10%	-0.12%	-0.17%	-0.06%
Spain	0.19%	0.16%	0.22%	0.43%	0.47%	0.39%	-0.01%	-0.10%	0.08%
Sweden	-0.01%	0.01%	-0.05%	0.18%	0.27%	0.07%	-0.19%	-0.21%	-0.15%
Switzerland	0.00%	-0.03%	0.03%	0.16%	0.28%	0.05%	-0.14%	-0.30%	0.00%
United Kingdom	0.00%	-0.02%	0.03%	0.19%	0.27%	0.10%	-0.15%	-0.26%	-0.03%
United States	0.03%	0.10%	-0.03%	0.06%	0.16%	-0.03%	0.01%	0.05%	-0.02%
Mean	0.03%	0.03%	0.03%	0.19%	0.28%	0.08%	-0.10%	-0.17%	-0.01%
Median	0.00%	0.01%	0.01%	0.18%	0.27%	0.05%	-0.14%	-0.20%	-0.02%

Notes: Welfare effects are reported as percentage changes in steady-state consumption equivalents following a one percentage point increase in the stock of immigrants. W_N denotes average native welfare, while W_{LN} and W_{HN} refer to low- and high-skilled natives. Scenario 1 assumes neutral skill composition; Scenario 2 (Scenario 3) considers an inflow twice as intensive in high-skilled (low-skilled) workers. Mean and median report cross-country averages.

1.4.3 Welfare Effects and Native-Immigrant Wage Gaps

Figure 1.5 shows, in several panels, the association between the simulated welfare effects of an increase in immigrants by 1 percentage point of the labor force on natives (vertical axis) and the pre-existing immigrant-native wage gaps across countries (horizontal axis, in percent). The panels show results from Scenario 1 (balanced immigration, left panels), Scenario 2 (high-skilled immigration, center panels) and Scenario 3 (low-skilled immigration, right panels). Additionally, we show the average welfare effect for all natives (in panels of the first row), the effect on low-skilled natives (in panels of the middle row) and the welfare effect for high-skilled natives in the panels of the bottom row. The first common feature that we notice from the panels is the positive association between the native-immigrant gaps and the welfare effect on average and on each group of natives. A larger gap between immigrants and natives in the labor market, corresponds to stronger incentives for firms to open vacancies as immigrants increase, and this increases labor demand, in net, and labor-market tightness, with positive effects on wages of native workers.

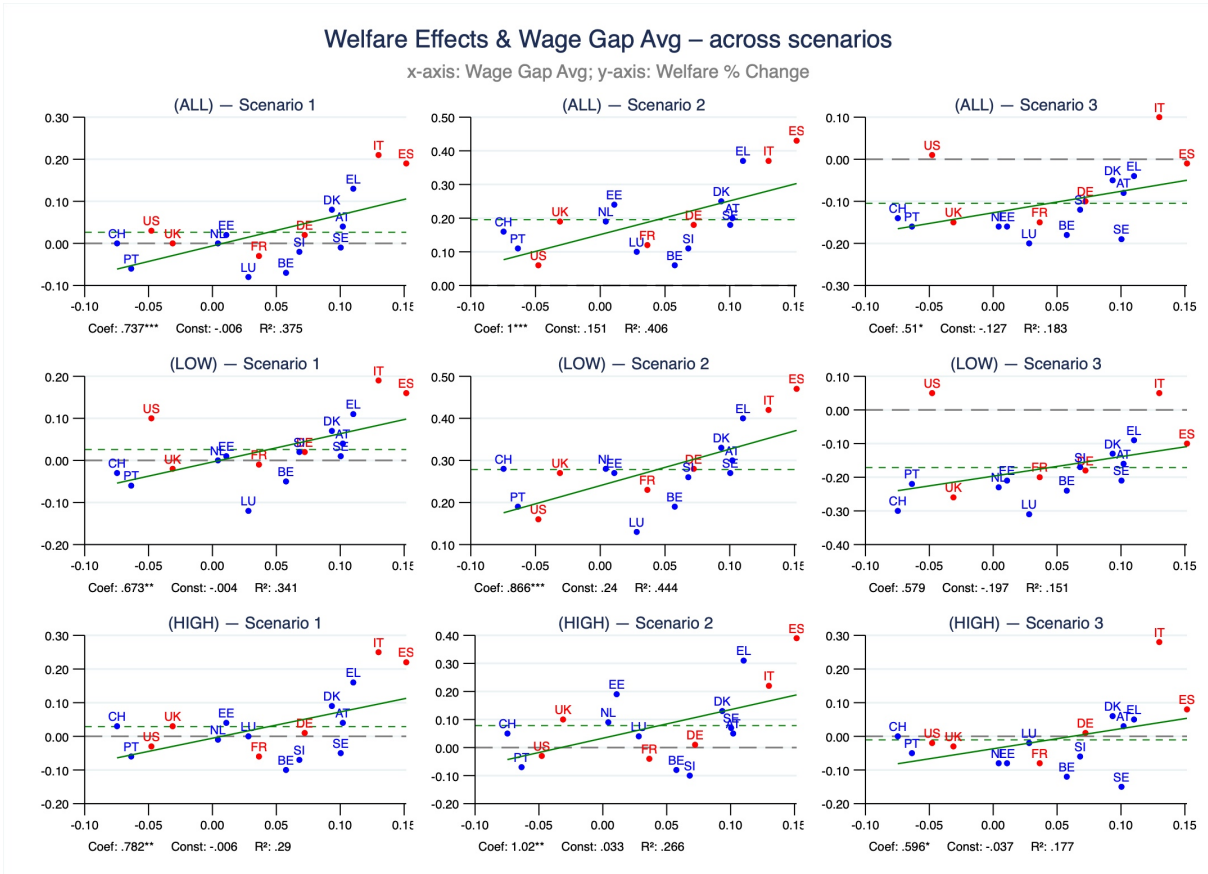
This pattern reflects a job-creation mechanism, which is central to search-and-matching models of the labor market, first identified by Chassamboulli and Palivos (2014) and then adopted in several studies, among which Battisti et al. (2018a). As immigrants are hired at wages that are low relative to their productivity, because of worse outside options, firms capture a larger share of the match surplus. Higher expected surplus raises vacancy creation, increases labor-market tightness, and improves job-finding prospects for all workers. Natives benefit both through higher employment probabilities and through positive equilibrium wage adjustments (Battisti et al., 2018a; Chassamboulli and Peri, 2020a).

The relationship between wage gaps and welfare gains weakens under Scenario 3, where immigration is predominantly low-skilled. In this case, the positive job-creation effect associated with lower immigrant wages is more likely to be offset by fiscal pressures

and distributional costs. More low-skilled immigrants imply lower contribution per person to the government (and to pay for public transfers) and hence a cost for natives. As a result, even when wage gaps are sizeable, the net welfare effect of low-skilled immigration may be smaller or negative.

Notice that in these panels Italy and Spain (and to a lesser extent Greece) are positioned at the top-right of each chart, as those are countries where the native-immigrant wage gap generates the largest positive job creation effects. Switzerland and Portugal are at the opposite ends with the smallest wage gaps and generally small consequences of immigration.

Figure 1.5: Relationship between wage gaps and welfare gains

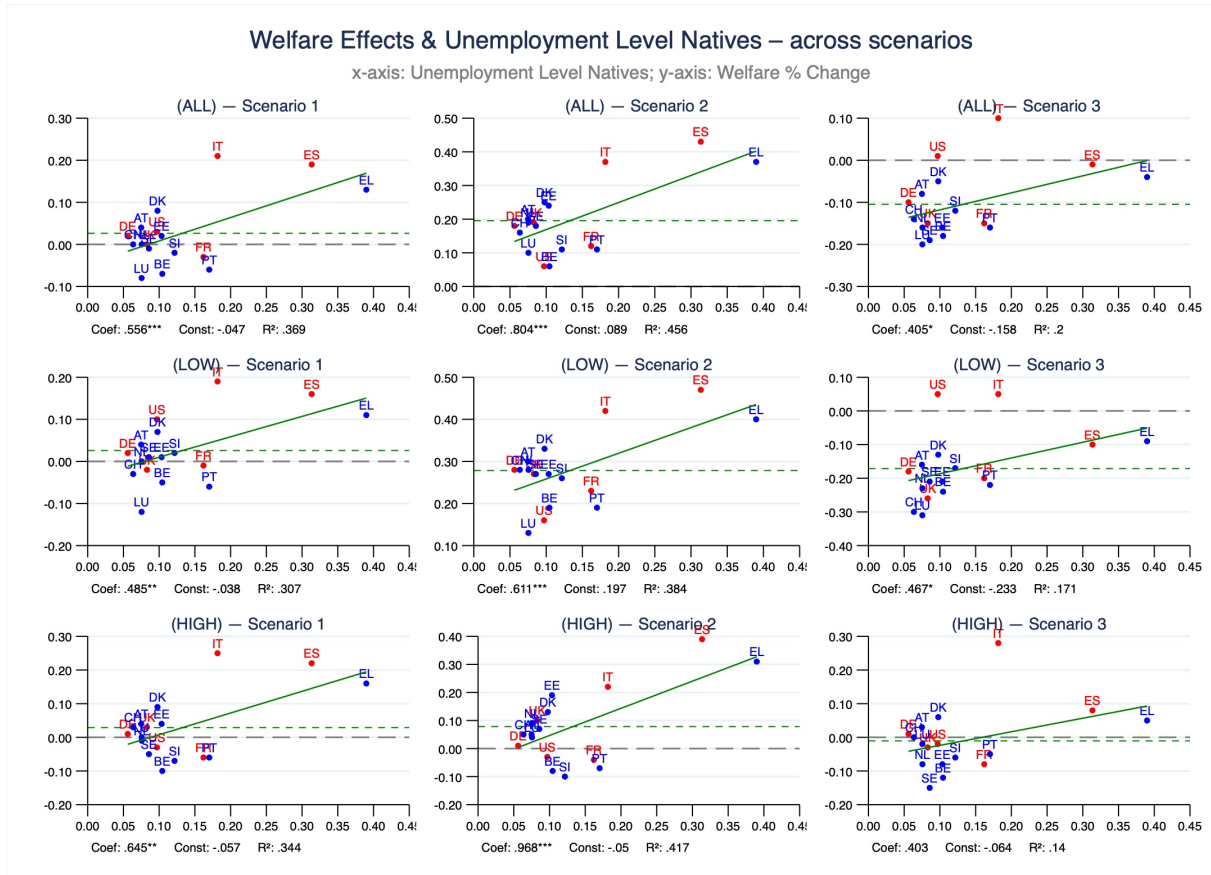


Notes: Each panel reports the relationship between native welfare changes and average immigrant–native wage gaps across countries. Welfare effects are expressed as percentage changes in steady-state consumption equivalents following a one percentage point increase in immigration. Panels correspond to Scenario 1 (neutral), Scenario 2 (high-skilled), and Scenario 3 (low-skilled) immigration, and are shown separately for all natives, low-skilled natives, and high-skilled natives. Solid lines report linear fits; dashed grey line indicates the zero; dashed green line indicates welfare percentage change mean.

1.4.4 Welfare Effects and Unemployment Rates of Natives

A second important structural labor-market characteristic, differing substantially across countries and with potentially important consequences in determining the effects of immigration, is unemployment. In this section, we investigate how the welfare effects of immigration differ between countries with higher and lower unemployment rates as measured for natives across countries. Figure 1.6 relates native welfare changes to native unemployment rates across countries, across different scenarios (column 1 to 3) and for different groups (total, low-skilled or high-skilled) across rows. A clear positive association emerges in all scenarios and for all groups: native welfare gains from immigration are larger in economies where native unemployment is initially higher.

Figure 1.6: Relationship between natives' unemployment level and welfare gains



Notes: Each panel reports the relationship between native welfare changes and average unemployment level of natives across countries. Welfare effects are expressed as percentage changes in steady-state consumption equivalents following a one percentage point increase in immigration. Panels correspond to Scenario 1 (neutral), Scenario 2 (high-skilled), and Scenario 3 (low-skilled) immigration, and are shown separately for all natives, low-skilled natives, and high-skilled natives. Solid lines report linear fits; dashed grey line indicates the zero; dashed green line indicates welfare percentage change mean.

The economic mechanism behind this relationship is due to the impact and relevance of the job-creation channel, highlighted in the model. When the unemployment rate is higher, the impact of immigrants on vacancy creation is stronger: an increase in firms' expected surplus translates into stronger incentives to post vacancies, larger improvements in job-finding probabilities, and more pronounced welfare gains for natives who transition from unemployment to employment.

Immigration affects this channel by raising the expected match surplus of firms, stimulating them to create more job openings. Some of these openings go to natives, increasing labor-market tightness, with stronger effects when unemployment is initially high. This is the main channel. A second channel is fiscal, operating mainly through the contribution of high-skilled immigrants. When unemployment rates are higher, unemployment-benefit payments form a significant part of redistribution, since they flow mainly to less-skilled workers, who face higher equilibrium unemployment. In this case, high-skilled immigrants help pay for unemployed natives, reducing the fiscal burden on the rest of the native population.

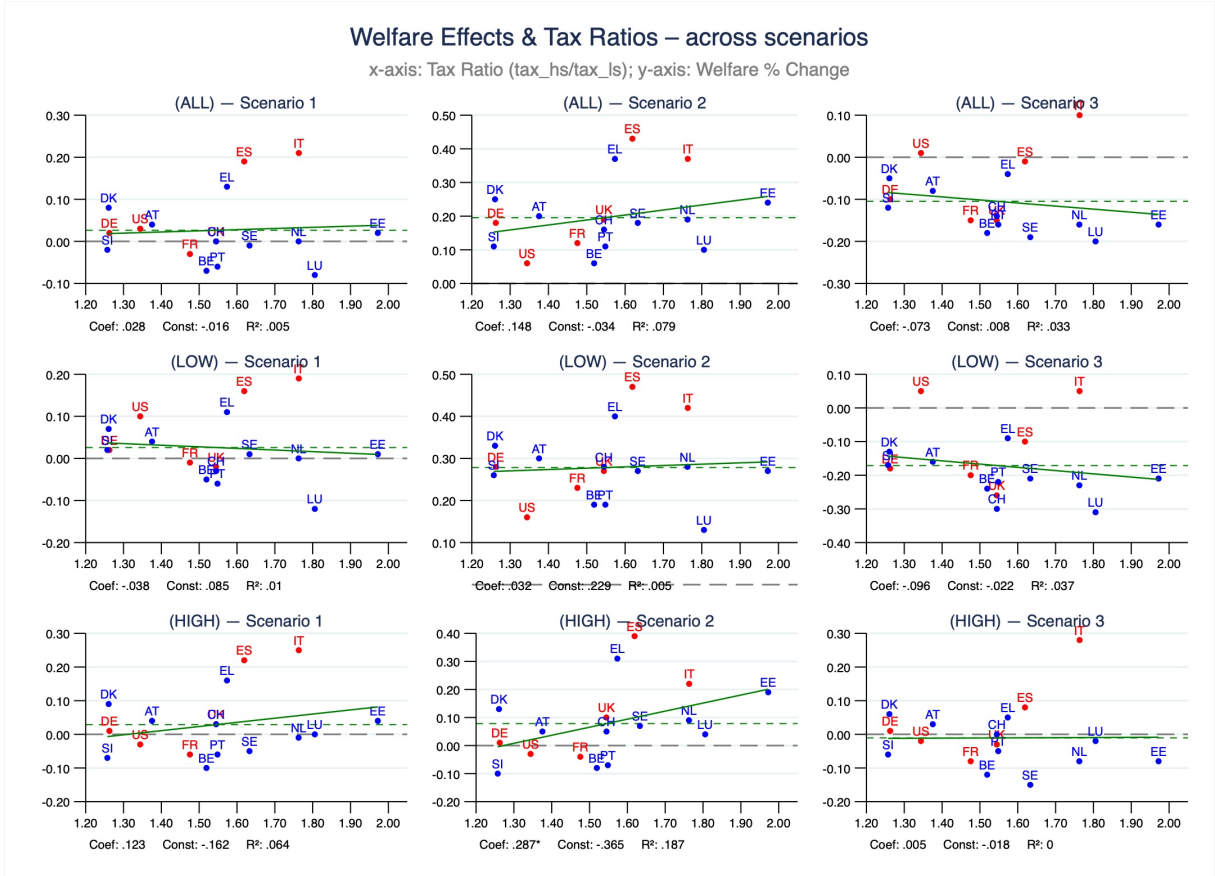
A feature of the panels in Figure 1.6 is a clustering of countries around relatively low unemployment levels, where welfare effects tend to be modest and tightly grouped. Greece and Spain have a significantly higher unemployment rate than the rest and Italy, France and Portugal are the next group with high unemployment. Across the other countries, small differences in unemployment rates are associated with limited variation in welfare effects. By contrast, Greece and Spain, located further to the right of the distribution, show substantially larger welfare gains. Italy stands out as a notable outlier, where the very large immigrant–native wage gaps interact with the third largest unemployment rate for natives, producing these strong welfare effects. Portugal, with similar unemployment rates but much smaller native-immigrant wage gaps (as we saw in the previous section), does not experience high welfare gains relative to the average for any group and scenario.

1.4.5 Welfare Effects and Tax Progressivity

A significant innovation of this study is to consider more carefully the general equilibrium fiscal effect of immigrants in countries with progressive taxation, government transfers and pure public good provision. In this section we investigate the extent to which countries with different degrees of progressive taxation in our data also differ in terms of the welfare effects of immigration on natives. As we measure effective tax rates across educational groups, we capture the intensity of progressivity in a country as the ratio of the high-skilled to low-skilled tax rates.

Figure 1.7 examines how the welfare effects of immigration for natives vary with the degree of tax progressivity, measured by the ratio of high- to low-skilled labor tax rates. As usual, different columns represent different immigration scenarios (neutral, high- and low-skilled intensive, respectively, from left to right) and the different rows show the impact on average, low- and high-skilled, from top to bottom, respectively. The panels show the relationship between tax progressivity and welfare outcomes, with patterns that differ across skill groups and immigration scenarios.

Figure 1.7: Relationship between tax ratio and welfare gains



Notes: Each panel reports the relationship between native welfare changes and tax ratios across countries. Welfare effects are expressed as percentage changes in steady-state consumption equivalents following a one percentage point increase in immigration. Panels correspond to Scenario 1 (neutral), Scenario 2 (high-skilled), and Scenario 3 (low-skilled) immigration, and are shown separately for all natives, low-skilled natives, and high-skilled natives. Solid lines report linear fits; dashed grey line indicates the zero; dashed green line indicates welfare percentage change mean.

First, higher tax progressivity is associated with larger average native welfare gains under the high-skilled immigration scenario (Scenario 2), while the low-skilled immigration scenario implies lower average native gains for countries with higher progressivity. This is because when immigration is concentrated among high-skilled workers, a progressive tax structure implies that a larger share of the fiscal burden will be shouldered by the incoming immigrants, relative to natives. As a result, a disproportionate part of the fiscal cost of redistribution is carried by the new immigrants, allowing natives to experience a lower tax burden on average. Additionally, from the middle and bottom panels we see that fiscal gains from sharing the burden benefit especially high-skilled natives, in high redistributive countries, as they were carrying a larger part of the burden.

The second result is that the same fiscal mechanism operates in the opposite direction when immigration is predominantly low-skilled. Under Scenario 3 (the right column of panels in Figure 1.7), an increase in lower-skilled immigrants, combined with higher tax progressivity, is associated with more negative welfare effects on average (top panel) and especially for low-skilled natives (middle panel). In this case, the inflow of low-skilled immigrants expands the pool of benefit recipients from the government redistribution, while contributing relatively less to the tax revenues. The resulting fiscal adjustment reduces the benefits from progressive taxation for low-skilled native workers, who already face weaker labor-market outcomes, and on average progressive taxation tends to amplify the adverse distributional effects of low-skilled immigration on low-skilled natives.

Finally, skill-neutral migration implies no correlation between progressivity and welfare effects on average, as in this case most countries experience small-to-positive welfare effects

and the fiscal burden on natives is not changed.

Taken together, these results highlight that tax progressivity plays an important role in shaping the average and distributional consequences of immigration. Rather than uniformly mitigating or amplifying welfare effects, progressivity reallocates the fiscal incidence of immigration shocks across skill groups. High-skilled immigration in progressive systems tends to redistribute fiscal costs toward immigrants, benefiting all natives and especially high-skilled workers, while low-skilled immigration in the same systems shifts fiscal pressure toward low-skilled natives, reducing their welfare and average welfare relative to low-redistribution countries.

1.4.6 Welfare Effects and Size of the Public Sector

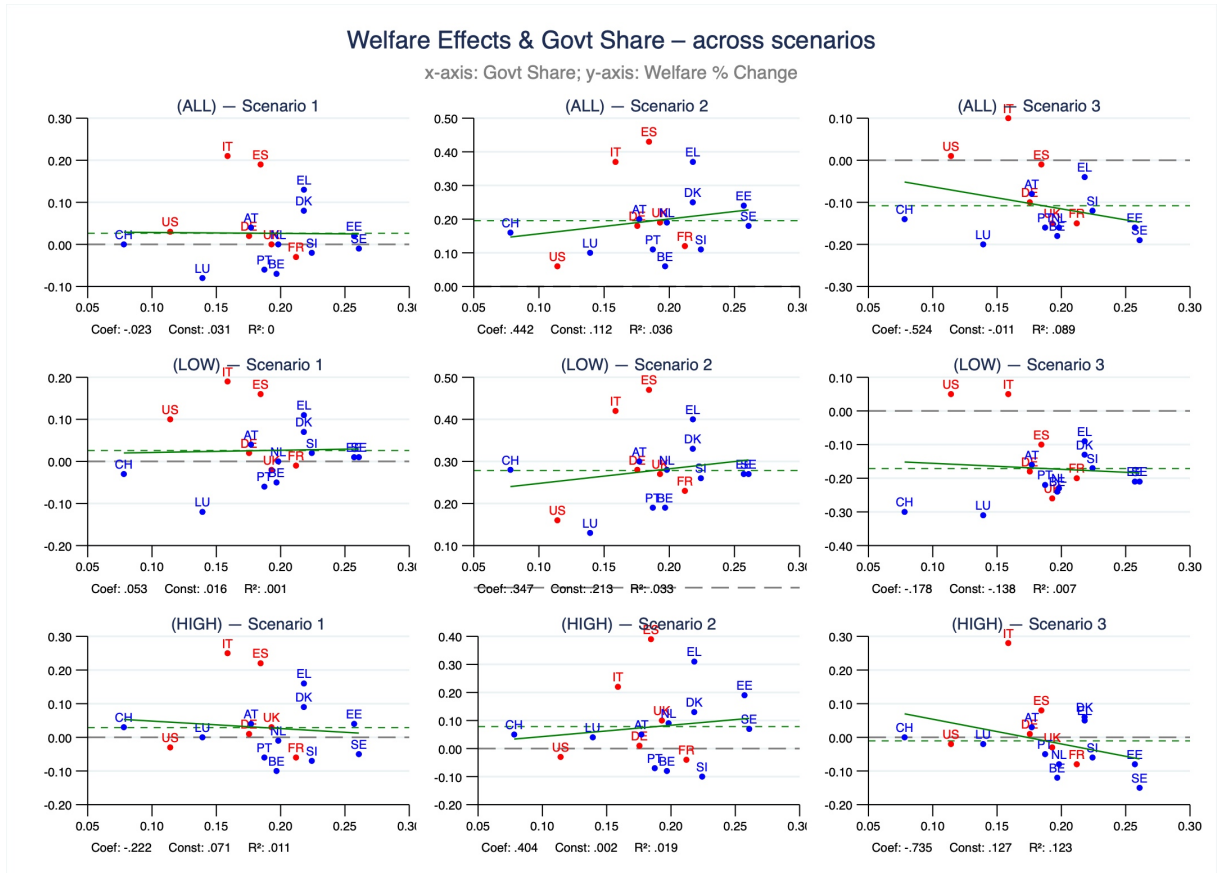
The final relation that we show is between the welfare effects of immigration and the size of the government sector, measured using government expenditures as a share of GDP. The usual structure of the panels, with different columns representing different immigration scenarios (neutral, high-skilled, and low-skilled intensive, from left to right) and different rows showing the impact on average, low-skilled, and high-skilled natives (from top to bottom), is shown in Figure 1.8.

Under high-skilled immigration (Scenario 2), countries with a larger government share tend to experience larger welfare gains for natives, both for high-skilled and low-skilled workers, in a similar way. This pattern reflects the interaction between immigration and the scale of public redistribution. When government redistribution and provision of public goods (a role that is combined in the size of government) is larger, a significant fraction of output is channeled through the public sector. An inflow of high-skilled immigrants expands the tax revenues and allows part of the fiscal burden associated with maintaining a large public sector to be shifted to immigrants and implies that natives (over-represented among less skilled) receive more of those transfers. Additionally, because the pure public good $\bar{g}$ is fixed in aggregate and provided by the government, immigration broadens the tax base that finances it. The fiscal cost per native is thereby reduced, lowering the equilibrium labor tax rates required to balance the budget and raising natives' take-home wages. Both effects help natives and amplify the positive welfare effects of immigration.

By contrast, under predominantly low-skilled immigration (Scenario 3), the relationship reverses. In countries with a larger public sector, low-skilled immigration is associated with more negative welfare effects for natives. When government expenditure is high, a low-skilled inflow increases fiscal pressure on natives by raising benefit expenditures and contributing relatively less to tax revenues. As a result, the adjustment required to finance existing public spending amplifies the negative welfare effects for natives, especially for low-skilled workers.

The qualitative relation of welfare effects to government size is similar to that observed for tax progressivity. However, the underlying mechanism is somewhat distinct. Government size captures the scale of public transfers, including pure public goods whereas tax progressivity captures its difference across skill groups. A larger government magnifies the fiscal consequences of immigration depending on the skill composition of the inflow, but does not by itself determine how the fiscal adjustment is distributed between natives and immigrants. Nevertheless, since in aggregate the government system redistributes from richer to poorer, increasing its size increases the redistribution. Government size shapes the overall exposure of native welfare to immigration through the size of the public budget, while tax progressivity governs the distributional channel through which immigration affects different skill groups.

Figure 1.8: Relationship between government share and welfare gains



Notes: Each panel reports the relationship between native welfare changes and government share across countries. Welfare effects are expressed as percentage changes in steady-state consumption equivalents following a one percentage point increase in immigration. Panels correspond to Scenario 1 (neutral), Scenario 2 (high-skilled), and Scenario 3 (low-skilled) immigration, and are shown separately for all natives, low-skilled natives, and high-skilled natives. Solid lines report linear fits; dashed grey line indicates the zero; dashed green line indicates welfare percentage change mean.

1.5 Welfare Effects using the 2019-2024 Immigrants' Skill Composition

In this section, we move beyond the hypothetical scenarios analyzed in Section 1.4 and we simulate the welfare effects of a one percentage-point increase in the stock of foreign-born workers using the actual immigrants' skill composition experienced by the receiving countries in recent years. For each country, we measure the skill composition, in terms of share of non-tertiary educated (low-skilled) and tertiary educated (high-skilled) migrants of the 2019-2024 inflows using data on recent immigrants (arrived within the five years preceding the survey) from National sources. The simulation shows the welfare effect of a one percentage-point increase in the labor force from immigrants with such a skill composition.⁸

The skill composition of recent immigrant inflows is measured using the European Union Labour Force Survey (EU-LFS), which provides a consistent cross-country definition of educational attainment and a harmonized variable for year of arrival. We identify recent immigrants as foreign-born individuals who report having arrived in the host country less than five years earlier (years since arrival categories: 0 through 4, or the grouped category Y0-4). For the United Kingdom we use the UK Labour Force Survey, which applies the same International Standard Classification of Education (ISCED) mapping used in the EU-LFS and records duration of residence in comparable brackets. For the United States we use the IPUMS extract (ACS), defining recent immigrants analogously as foreign-born individuals who entered the country within five years since the survey. In all three sources, individuals are classified as high-skilled if they hold a tertiary degree and as low-skilled otherwise. These observed skill shares replace the hypothetical compositions of the previous section in assessing how the immigration experienced by OECD countries affected native welfare within our calibrated framework and period.

Table 1.7 shows in columns 3 and 4 such skill composition for the recent immigration flows (share with lower and higher education). For comparison, as the relative impact of immigrants will depend on the existing skill composition of residents, we show the skill composition of total resident population in 2019, in columns 1 and 2. A clear pattern emerges in comparing the skills of immigrants and of previous residents, which is consistent with what is described in most of the literature on migration (Grogger and Hanson, 2011a; Docquier et al., 2014b). In the large majority of countries, recent inflows of immigrants are substantially more skill-intensive than the resident population. On average, the share with tertiary education among recent immigrants was 44.3 percent across the destination countries, compared with only 31.5 percent in the 2019 resident population. Immigrants, in short, represent an increase in the skill intensity of the labor force of the receiving country.

Looking at individual countries, we notice that the skill intensity of immigrants was particularly strong for the United Kingdom, where nearly 80 percent of 2019-2024 arrivals had a tertiary degree. Consistent with the shift to a strict points-based immigration

⁸Across the 17 countries, the cumulative 2019-2024 inflow as a share of the 2019 working-age population ranges from 0.8% in Greece to 20.8% in Luxembourg (a small-economy outlier; the next-highest is Switzerland at 9.9%), with a cross-country mean of 5.4%, roughly five times the simulated 1pp shock. The largest recipients are Luxembourg, Switzerland, Germany, the Netherlands and Austria, all above 6%; the bottom three are Greece, Italy and Slovenia, all below 2%. Because the welfare effects in Table 1.8 are normalized to a fixed 1pp shock, the implied effects under each country's actual flow size scale approximately with this magnitude, so countries with larger inflows experienced welfare gains several times the per-pp numbers, while countries with sub-1pp inflows experienced more muted effects. Inflow magnitudes are computed from the same data sources used below, using year of first arrival.

system, following Brexit and the end of free mobility with the EU in January 2021, the UK explicitly selected immigrants on qualifications and salary thresholds⁹. Luxembourg, Switzerland and Denmark were other countries in which the high-skilled share of inflows exceeded 55 percent.

These patterns likely reflect a combination of selective immigration policies, higher international mobility of university-educated workers, general educational improvements across the young cohorts of many sending countries, and the increase in destination-specific demand for skilled labor (as already argued by [Docquier et al. \(2014a\)](#) and [Beerli et al. \(2021\)](#)).

Greece and Slovenia are the only countries where recent immigrant flows were actually slightly less skill-intensive than the resident population, with the high-skilled share among new arrivals below 22 percent in both cases. Italy shows relatively low skill intensity of immigrants, yet they remain more skilled than its resident population (22 versus 16 percent high-skilled). As the skill composition of the inflow of immigrants relative to the existing population is a key determinant of whether immigration generates positive welfare effects for natives (through productivity externalities and fiscal effects), this distribution suggests a prevalence of positive effects driven by high skill intensity.

Table 1.7: Skill composition of resident population and recent immigrant flows

	2019 Population Skill Shares		2019–2024 Immigrant Flow Skill Shares	
	Lower	Higher	Lower	Higher
Germany	0.740	0.260	0.650	0.351
Spain	0.655	0.346	0.594	0.407
France	0.690	0.310	0.580	0.420
Italy	0.837	0.163	0.780	0.220
United Kingdom	0.619	0.381	0.201	0.799
United States	0.690	0.310	0.636	0.364
Austria	0.702	0.298	0.566	0.434
Belgium	0.652	0.349	0.561	0.439
Switzerland	0.595	0.405	0.369	0.631
Denmark	0.659	0.341	0.449	0.551
Estonia	0.645	0.355	0.429	0.571
Greece	0.757	0.243	0.786	0.214
Luxembourg	0.644	0.356	0.310	0.690
Netherlands	0.629	0.371	0.538	0.462
Portugal	0.797	0.203	0.666	0.334
Sweden	0.616	0.384	0.545	0.455
Slovenia	0.715	0.285	0.808	0.192
Average	0.685	0.315	0.557	0.443

Notes: The first two columns report the share of low and high-skilled individuals in the total resident population (natives and immigrants) as of 2019. The last two columns report the skill composition of immigrant inflows observed between 2019 and 2024. Low-skilled workers are defined as those without tertiary education. Source: EU-LFS (European countries), IPUMS-ACS (United States).

Table 1.8 reports the country-specific welfare effects of an increase in immigration by

⁹The UK Labour Force Survey uses the same ISCED-based education classification and comparable duration-of-residence categories as the EU-LFS, to which the UK contributed until 2020. The high skill intensity of post-2021 UK inflows is consistent with the introduction of the points-based immigration system, which selects on qualifications and salary thresholds.

one percentage point of the labor force, with the observed 2019–2024 skill composition. Because the simulation holds the total size of the inflow constant, at one percentage point of the receiving country labor force, cross-country differences in welfare effects reflect only variation generated by differences in receiving-country fundamentals and in the skill composition of the net immigration flow. The simulated results do not reflect differences in the scale of immigration ¹⁰.

Several findings stand out from Table 1.8. First, the average welfare effects for native residents are positive in the large majority of countries (15 out of 17), with a cross-country mean welfare gain of 0.17 percent for natives. This is substantially larger than the near-zero average effect under skill-neutral inflows (Scenario 1 in Table 1.6, where the mean gain is 0.03 percent), and closer to the gains obtained under the hypothetical high-skilled scenario (Scenario 2, mean 0.19 percent). The similarity is consistent with the data: as documented above, recent immigrant flows have been considerably more skill-intensive than the resident population in most countries.

Second, some countries are especially notable for experiencing large welfare gains from immigration. The United Kingdom stands out as the country with the largest and positive welfare effect (0.49 percent for an average non-migrant resident and a very significant +0.73% for less-skilled), consistent with the exceptionally high-skilled composition of its recent (post-Brexit) immigrant inflows. Luxembourg, Estonia, Denmark, Italy and Spain also display sizeable gains, ranging from 0.26 to 0.41 percent. The reasons are somewhat different across them. While Luxembourg, Estonia and Denmark benefit from the productivity boost and fiscal contribution of their extremely high-skilled immigration, Italy and Spain benefit from the boost to job creation from immigrants, due to their higher unemployment rates and larger surplus created by immigrants (linked to the large immigrant-native wage differential).

The United States exhibits a modest positive effect (0.04 percent), in line with the small effects found across all three stylized scenarios in Table 1.5, reflecting both narrow native–immigrant wage gaps, small differences in this period between the skill composition of immigrants and the existing population, and a limited public sector.

Belgium and Slovenia are the only two countries where average native welfare is slightly negative, a result that in Slovenia is driven by the low skill intensity of its recent inflows, the only country alongside Greece where the high-skilled share of recent arrivals falls below the baseline population share. Greece, despite also having a less-skill-intensive recent inflow, retains a small positive welfare effect (+0.07%), driven by its very high native unemployment rate, which amplifies the job-creation channel and offsets the weaker skill-composition channel.

The third consistent pattern to be noted across countries is that low-skilled natives tend to benefit more than high-skilled natives (on average by 0.24 versus 0.07 percentage points), mirroring the distributional pattern of Scenario 2. This reflects the productivity spillovers and complementarities generated by high-skilled immigration, which raise the marginal product of less-skilled labor more than that of high-skilled labor, combined with the fiscal relief that higher-skilled immigrants provide relieving high-skilled natives of part of their tax burden. The job-creation effect also contributes to this asymmetric pattern, as it tends to be especially strong in labor markets with higher unemployment rates, which typically characterize the low-skilled segment.

¹⁰This differs from the approach in Battisti et al. (2018a), where simulations were based on actual inflow sizes, making it harder to disentangle the role of country characteristics from that of the magnitude of the shock.

Table 1.8: Welfare effects of a 1 pp increase in immigration: 2019–2024 flow skill composition

Countries	Flows 2019–2024		
	W_N	W_{LN}	W_{HN}
Austria	0.18%	0.26%	0.05%
Belgium	−0.01%	0.07%	−0.09%
Denmark	0.30%	0.40%	0.15%
Estonia	0.32%	0.37%	0.25%
France	0.06%	0.14%	−0.05%
Germany	0.10%	0.16%	0.01%
Greece	0.07%	0.04%	0.12%
Italy	0.27%	0.29%	0.24%
Luxembourg	0.41%	0.59%	0.10%
Netherlands	0.10%	0.15%	0.05%
Portugal	0.12%	0.21%	−0.07%
Slovenia	−0.11%	−0.15%	−0.06%
Spain	0.26%	0.25%	0.27%
Sweden	0.07%	0.11%	0.00%
Switzerland	0.24%	0.42%	0.07%
United Kingdom	0.49%	0.73%	0.21%
United States	0.04%	0.12%	−0.03%
Mean	0.17%	0.24%	0.07%

To deepen our understanding of the mechanisms behind these welfare effects, we decompose the change in native welfare into four channels: pre-tax labor income (driven by changes in pre-tax wages and unemployment rates), the labor tax channel (capturing changes in the effective tax burden on labor), capital income (changes in capital productivity), and transfers (changes in public good provision and welfare transfers). Figure 1.9 presents this decomposition graphically for the six largest economies in our sample, while the full decomposition for all seventeen countries is reported in Table 1.A2 and Figure 1.A1 in the Appendix. In what follows we first describe the average patterns across countries, and then use Figure 1.9 to highlight how channels combine differently across individual countries.

On average across countries, the pre-tax labor income channel is the dominant source of welfare gains for non-migrants (0.11 percentage points out of a total of 0.17). This is generated by the increase in labor productivity due to the positive productivity effect of high-skilled immigrants and to the job-creation effect. The second positive contributor to native welfare is the increase in capital income (+0.04), raised by the higher labor supply and productivity. Finally, the labor tax channel (+0.03) implies an average decline of labor taxes for natives, as fiscal burden partially shifts to immigrants. Transfers contribute very little to the average effect.

This aggregate picture masks important differences across skill groups. For lower-skilled natives, pre-tax labor income accounts for almost the entire welfare gain (0.20 out of 0.24 percentage points), with capital income providing a modest additional contribution (0.06). This reflects the complementarity and productivity spillovers generated by the relatively skill-intensive inflows as well as from the job-creation effect among low-skilled, due to firms' new job postings, stimulated by the presence of immigrants, which increases

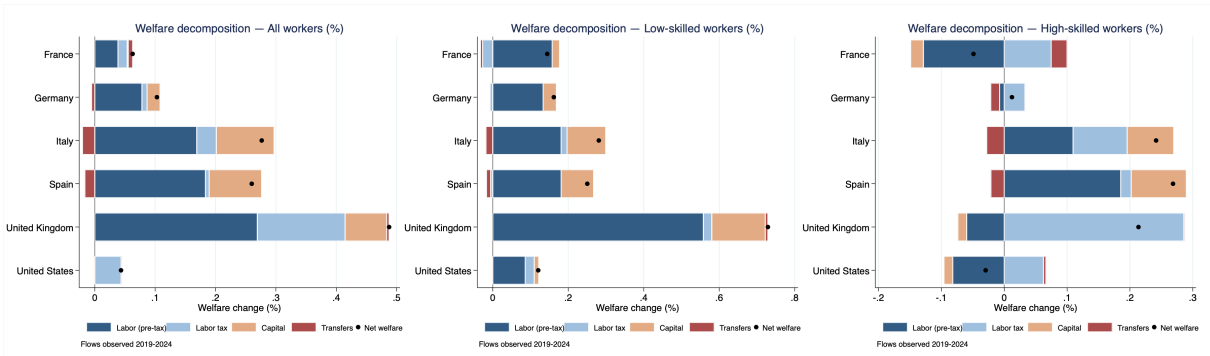
labor demand and wages. For higher-skilled natives, by contrast, the pre-tax labor income effect is much smaller and, on average, almost null (-0.01), as the inflow of similarly educated immigrants increases competition within the high-skilled segment and offsets the other productivity benefits. Their welfare gains instead come almost entirely through the labor tax channel (+0.07), which captures the fiscal relief that arises when higher-skilled immigrants share the tax burden associated with financing redistribution. This pattern is consistent with the role of tax progressivity and hence stronger where the tax rate differential between high- and less-skilled is higher.

Turning to individual countries, Figure 1.9 reveals how differently the four channels contribute to the effects across the six largest economies analyzed.

The United Kingdom displays the most striking pattern, in line with what we said describing the average effects. Its recent inflows have been very high-skilled according to our data, with nearly 80 percent high-skilled. Such inflow generated the largest overall welfare gain among all countries in the sample (0.49 percent). For low-skilled British native residents, the dominant channel was the increase in pre-tax labor income (+0.56 percentage points), reflecting strong complementarity and productivity effects from a highly educated inflow. For high-skilled natives, instead, the pre-tax labor income effect was slightly negative (-0.06), as the large number of skilled new arrivals competed directly with incumbent skilled workers. This small loss, however, was more than offset by a large positive labor tax effect on welfare (+0.29) on highly skilled individuals, indicating that the reduction in their fiscal burden played a crucial role in redistributing the gains from immigration toward high-skilled natives through reduced tax burdens. The United Kingdom thus illustrates a case where the fiscal channel is important in ensuring that both skill groups benefit from high-skilled immigration.

Italy and Spain present different patterns. In both countries, the pre-tax labor income channel is positive for all native groups, including high-skilled workers. In Italy, the capital income channel is substantial (0.10 for all natives), consistent with the country's high capital share, which amplifies production complementarities. Both high-skilled and low-skilled Italian natives experience positive pre-tax labor income effects (respectively +0.19 and +0.11) resulting from the relatively similar skill composition between immigrants and Italian residents, combined with the large native-immigrant wage gaps documented in Section 2, which boost job creation and raise the marginal product of all native labor. Spain displays a broadly similar pattern, with the notable feature that welfare effects are even across skill groups (0.25 for low-skilled, 0.27 for high-skilled), suggesting that the channels roughly balance across education levels. France, Germany and the United States illustrate cases where the overall effects are more modest. In France, the pre-tax labor income channel is positive for low-skilled natives (0.16) but negative for high-skilled natives (-0.13), generating a total welfare effect for high-skilled natives that is slightly negative (-0.05). The labor tax channel partially offsets this (0.07 for high-skilled), but not enough to produce a net gain. Germany follows a qualitatively similar pattern, though with smaller magnitudes, reflecting the more moderate skill intensity of its recent inflows relative to France. The United States stands apart for the very small magnitude of virtually all channels: the largest single component is the pre-tax labor income effect for low-skilled natives, at just 0.09 percentage points. This smaller response reflects the combination of skill balance between immigrants and existing population (at least in this period), narrow native-immigrant wage differentials (in fact slightly reversed for the high-skilled, where immigrants earn about 6% more than natives, so the job-creation channel acts as a small drag rather than a boost for that group), a small public sector and limited tax progressivity, all of which were already identified in the stylized scenarios of Section 4.

Figure 1.9: Welfare decomposition by channel: selected countries (DE, ES, FR, IT, UK, US)



Notes: Each panel reports the welfare decomposition for native workers following a one percentage point increase in immigration, using skill shares observed in 2019–2024 immigration flows. Welfare effects are expressed as percentage changes in steady-state consumption equivalents and decomposed into four channels: labor income (pre-tax), labor tax, capital income, and transfers. Positive components are stacked rightward from zero; negative components are stacked leftward. The black dot indicates the net welfare effect (sum of all components). Panels correspond to all natives, low-skilled natives, and high-skilled natives.

Taken together, these results show that the welfare effects identified under the high-skilled immigration scenarios (Scenario 2) of Section 4 are similar to those obtained when the model is simulated using flows that mirror the actual country-specific skill compositions of recent years. The broadly positive effects observed across most countries reflect the skill-intensive composition of recent flows, but the cross-country heterogeneity in the magnitude and distribution of gains underscores that receiving-country fundamentals (wage gaps, unemployment conditions, and the structure of taxation) remain important in shaping how immigration translates into native welfare.

1.6 Conclusions

This paper analyzes the welfare effects of immigration on natives in a quantitative search-and-matching framework with labor-market frictions, which is among the first to additionally include fiscal redistributions and the impact on the public sector. This model allows us to identify and discuss how immigration affects natives through labor-market channels (complementarity, productivity and job creation effects) and fiscal channels (shift of tax burden and of generosity of transfers).

Building on [Battisti et al. \(2018a\)](#) and [Docquier et al. \(2014b\)](#), the model additionally includes a more comprehensive tax and government sector, allowing it to vary both in size and progressivity through skill-specific effective labor taxes. We also incorporate capital taxation in a simple way. These features generate multiple channels through which immigration affects wages, employment, fiscal balances and native welfare, but we can identify three crucial features that strongly help predict the welfare effect of immigrants on natives.

The first is that the skill intensity of immigrants is crucial (as already well known) in generating welfare effects. Skill-neutral immigration still usually has small and positive welfare effect on natives, but it is skill-intensive immigration that shows the largest and most positive effects.

The second is that two labor-market features deeply shape the welfare response through their effect on pre-tax labor income: the native-immigrant wage gap and the resident unemployment level. Larger values of both stimulate the job-creation effect of immigrants and amplify its impact on native welfare.

The last point is that higher tax progressivity, and to a lesser extent a larger government size, are associated with larger beneficial fiscal effects on natives under high-skilled immigration, and with negative fiscal effects under unskilled immigration. Together, these mechanisms help rationalize the cross-country heterogeneity observed in the results: migration shocks of similar aggregate size can generate different wage, employment, and welfare responses depending on pre-existing wage gaps, unemployment differentials, tax rate differentials and differences in the skill intensity of immigration itself.

These patterns are confirmed when we investigate the model’s implications of a migration shock that mimics the skill composition of actual 2019–2024 immigration flows. In most countries, these flows are considerably more skill-intensive than the resident population. Under these inflows, native welfare rises in nearly all countries, with a mean effect of +0.17 percent. A decomposition of welfare effects reveals that the transmission channels differ across skill groups. Low-skilled natives benefit predominantly through pre-tax labor income and capital income, as the complementarity and productivity effects of skill-intensive immigration raise the marginal product of less-educated labor. They also benefit, especially in countries with higher unemployment rates and larger native-immigrant wage gaps, from the job-creation effects that immigrants trigger. High-skilled natives, by contrast, gain mainly through the labor tax channel: as high-skilled immigrants enter the tax base, they absorb part of the cost of financing redistribution, reducing the effective burden on incumbent skilled workers. In terms of pre-tax labor productivity, high-skilled natives are usually not affected much, as the negative competition effect (from higher supply of high-skilled labor) is roughly balanced by the positive productivity effect of high-skilled labor on TFP. The cross-country variation in these effects reinforces the central message of the paper. Countries such as the United Kingdom, where recent inflows are overwhelmingly high-skilled and native-immigrant wage gaps are moderate, experience significant gains driven by fiscal relief for skilled natives, while unskilled natives benefit in their pre-tax wages. Italy, with its wide wage gaps and high capital share, benefits through strong job-creation and complementarity effects. The United States, characterized by narrow wage differentials and a small public sector, experiences small average effects regardless of the composition of the inflow.

Taken together, these findings highlight that the same-size immigration shock can generate different welfare responses across countries and across skill groups. By modeling these channels together in a single quantitative framework, the paper provides an updated and unified interpretation of cross-country heterogeneity in the welfare effects of immigration by considering different immigration compositions and different labor market and fiscal conditions.

Besides this methodological contribution, a key message emerging is that, in this multi-channel analysis considering the range of immigration flows experienced by European countries and the US between 2019–2024 and their economic and fiscal fundamentals, the welfare impact of immigration on natives has been overwhelmingly positive, for both skilled and unskilled groups.

Chapter 2

The Fiscal Impact of Immigrants: Immigration Policy and Self-Selection

2.1 Introduction

A particularly salient facet at the core of policy discussions and socio-economic debates in Europe revolves around the fiscal impact of immigrants on destination countries. This paper delves into the complex interplay between immigration policy and migrant self-selection in destination countries, aiming to study their combined impact on the fiscal landscape of European countries.

While much of the existing literature treats these two critical elements independently, this study seeks to integrate them into a single analytical framework. The argument appears simple: assess whether immigrants are net contributors or net beneficiaries in the public budget. However, the reality is far more intricate. While immigration undeniably shapes the economic, social, and fiscal landscapes, the exact nature and magnitude of its impact remain subject of contention.

Some studies present immigrants as net contributors, enhancing public finances and enriching the destination country they reach. Others denote them in a more neutral or even negative fiscal light, suggesting that their demands on public resources offset, or even surpass, their contributions. Findings from various studies present several results, influenced by diverse methodologies, contexts, and temporal factors. Some evidence suggests that migrants, especially from the European Economic Area, boost the public finances of their adoptive European nations, contributing more than they extract. The UK serves as an example, reflecting a net positive impact of such migratory inflows ([Dustmann and Frattini, 2014b](#)). Yet a complementary body of research finds a more tempered fiscal contribution, with immigrants' net impact on GDP appearing minimal, or even marginally negative in certain contexts such as the case of France ([Chojnicki and Ragot \(2016\)](#)).

A central theme that emerges from these varying narratives is the role of self-selection in migrant populations, deeply intricately linked with the prevailing immigration policies of host countries. The policies set by host countries don't just control the number of immigrants but heavily influence the kind of individuals who choose to migrate. Such policies, depending on their design and implementation, can attract a diverse range of immigrants, from high-skill professionals to low-skill laborers, each bringing their unique fiscal implications. Therefore the interplay between immigration policy and self-selection largely governs the skill composition of incoming migrants. This, in turn, shapes their subsequent tax contributions and their demand for public resources in the host nation. A country attracting a

large number of high-skill migrants, for instance, may benefit from increased tax revenues and innovation, while also potentially facing challenges related to wage compression or sectoral imbalances. On the other hand, countries receiving a significant influx of lower-skilled migrants might benefit from labor-intensive sectors but struggle with issues related to social integration and demands on public services.

This project aims at analyzing this connection. I propose a unified approach that combines these two critical elements in a general equilibrium analysis in order to address this relationship. Using a structural model calibrated with data from EU-SILC, I aim to contribute to the complex topic of immigrants' fiscal influence in Europe by examining how immigration policies shape migrants self-selection, which in turn ultimately impacts the fiscal outcome of the destination countries.

Literature and Contribution - A large and growing literature examines the fiscal impact of immigration, yet findings remain much heterogeneous. Some studies document positive net contributions by migrants, particularly in contexts where immigrants are relatively young or highly skilled (Colas and Sachs, 2024b; Migration Advisory Committee, 2018; Dustmann and Frattini, 2014b). Others find more muted effects, with immigrants' fiscal contribution close to zero or even slightly negative, as illustrated for countries such as France and the United States (Bertoli and Stillman, 2019; Blau and Hunt, 2019; Chojnicki and Rabesandratana, 2018; Vargas-Silva, 2015). This wide divergence in findings underscores the complexity of assessing the fiscal consequences of immigration and points to important differences in analytic approach, empirical context and data.

A significant source of this heterogeneity arises from the methodological frameworks used, within the structural strand of the literature. Studies adopt either static or dynamic perspectives, each capturing different margins of the fiscal impact. Static analyses (Chojnicki (2013); Bogdanov et al. (2014)) provide a snapshot of current fiscal contributions and expenditures, offering a clear view of how immigrants interact with the public finances at a given point in time. In contrast, dynamic approaches such as Net Present Value calculations and Dynamic Applied General Equilibrium models (OECD (2013a), Hansen et al. (2017)), trace the long-term implications of immigration by modeling demographic change, labor-market trajectories, and future tax–benefit flows. These methodological differences naturally lead to different interpretations of the fiscal impact. In this paper, I adopt a static framework suitable for the current European context. It enables to focus on the fiscal footprint of today's migrant populations, based on their observed characteristics and immediate interaction with tax and transfer systems. This paper therefore concentrates on first-generation migrants, providing a clear insight into how newcomers engage with fiscal institutions before assimilation dynamics and intergenerational effects unfold.

Beyond methodological choices, an additional source of heterogeneity in the literature concerns differences in analytical focus. In particular, studies vary in how they conceptualize the determinants of migration decisions. Migration choices are shaped by differences across destinations in expected labor-market returns, tax burdens, access to transfers and public goods, and migration costs, all of which interact with individual characteristics such as skills, age, and family composition. Depending on which of these elements is emphasized, analyses highlight different mechanisms through which migration patterns and fiscal outcomes emerge. Some contributions focus primarily on institutional and policy features that alter the relative attractiveness of destinations such as Kancs and Lecca (2018a), Chassamboulli and Peri (2020b) and Mayda et al. (2022); while others emphasize how migrants sort across countries based on expected returns given their own characteristics, Battisti et al. (2018b), Migration Advisory Committee (2018). However, a

fully integrated approach considering both immigration policy and migrant self-selection remains underdeveloped: the contemporary economic literature indicates that while policy frameworks are evolving to address global labor market needs, individual migrant choices and characteristics are also dynamically interacting with these policies¹. This paper brings these elements together within a unified framework that models migration as a destination-choice problem, allowing policy environments to shape migrant selection through their effect on expected net returns and fiscal interactions.

The analysis delivers three main results. First, immigration policy affects fiscal outcomes through labor-market adjustments induced by policy-driven changes in migration costs that alter relative destination attractiveness, rather than through the direct change in the skill composition of inflows. Second, the fiscal consequences of this self-selection operate mainly through general equilibrium wage adjustments. Policies that attract migrants of a given skill type tend to compress wages in that segment, reducing tax revenues from those workers, while generating opposite effects for the complementary skill group. Third, these mechanisms generate substantial heterogeneity across destinations and spillovers across countries. Differences in production structure mediate how selection effects translate into wages and fiscal balances, while migration responses in one country affect outcomes elsewhere through reallocation of migrants within the integrated European labor market. Taken together, the results show that the fiscal impact of immigration policy emerges endogenously from the interaction between policy-induced selection, labor-market adjustment, and cross-country spillovers, rather than being determined solely by the intended skill targeting of migration reforms.

This paper contributes to the literature along three main dimensions. First, it relates to the growing body of work measuring the fiscal impact of immigration across countries by providing new evidence on migrants' household-level fiscal balances in a comparative European setting (Colas and Sachs, 2024b; Chojnicki and Rabesandratana, 2018). By focusing on detailed tax and benefit interactions, the analysis complements existing cross-country fiscal accounting exercises (Mariani et al., 2025; Dustmann and Frattini, 2014b). Second, the paper connects the literature on immigration policy and migrant selection to fiscal outcomes (Brinatti and Guo, 2023; Mariani et al., 2025). Rather than treating migration policy or migrant characteristics in isolation, this framework explicitly links destination-specific fiscal institutions to migrant self-selection, showing how policy environments shape the composition of migrant inflows and, through that channel, their fiscal contributions. Third, the paper contributes to the structural migration literature by embedding fiscal accounting within a destination-choice model (Battisti et al., 2018b; Chassamboulli and Peri, 2020b; Caliendo et al., 2023). This approach allows for a unified assessment of how migration policies affect selection patterns and fiscal balances simultaneously, bridging reduced-form fiscal analyses and structural models used to simulate policy counterfactuals.

The remainder of the paper is organized as follows. Section 2 presents the data and descriptive analysis, documenting cross-country patterns in migrant composition and fiscal outcomes. Section 3 introduces the theoretical framework that links immigration policy, migrant self-selection and household-level fiscal balances. Section 4 describes the calibration of parameters and discusses the main results from simulating policy counterfactuals. Section 5 concludes.

¹A recent exhaustive review is presented by Macaluso (2022)

2.2 Descriptive Analysis

2.2.1 Data

I use data from the European Union Statistics on Income and Living Conditions (EU-SILC), a harmonized survey administered annually by Eurostat that provides detailed information on income, taxes, transfers, and living conditions across European countries. EU-SILC is particularly well suited for the analysis of migrants' fiscal contributions, as it contains comprehensive data on both taxes paid and benefits received at the individual and household levels. The analysis relies on cross-sectional data from 2010 to 2019, covering five destination countries $j \in J$: Germany, France, Italy, Spain, and the United Kingdom (with UK data available up to 2018 due to Brexit).

EU-SILC reports information at both the individual level $i \in N_f \in \bar{I}$ and the household level $f \in N_f \in \bar{I}$, allowing for a detailed reconstruction of fiscal balances. Individuals are classified as migrants if they were born outside the European Union and migrated from a non-EU country. The analysis focuses exclusively on extra-EU migrants, excluding intra-EU movers who are subject to a common legal framework for mobility. This restriction allows the analysis to isolate the role of national immigration policies and fiscal institutions in shaping migrant selection and fiscal outcomes. For Germany, information on year of migration is missing between 2015 and 2019, hence for those years migrant status is proxied using citizenship information.

At the individual level, employment status is defined based on self-reported main activity, distinguishing between employed individuals $e = 1$ and non-employed individuals $e = 0$. Educational attainment is used to classify individuals into high-skill $s = 1$ and low-skill $s = 0$ groups, with tertiary education or higher defining high skill. Individual labor income is measured as the sum of employee cash or near-cash income, non-cash employee income, and cash profits or losses from self-employment, all recorded on a net basis. This aggregate measure captures total labor income $w_{i,j}(s, e)$ consistently across employment types.

The analysis then shifts to the household level, which constitutes the unit of fiscal accounting. To focus on first-generation migrant families, households are classified as migrant households if all adult parents in the household are extra-EU migrants. In practice, a household is defined as a migrant household when it includes at least one migrant parent and no native parent. This definition excludes households with mixed native-migrant parentage and allows the presence of children, who may be either foreign-born or native-born, while ensuring that the household's adult composition reflects first-generation migration. This classification isolates households whose economic behavior and fiscal interaction are driven by first-generation migrants rather than by second-generation dynamics. All remaining households are classified as native households. Migrant households are further characterized by skill composition: a household is defined as high-skill if the number of high-skill members is greater than or equal to the number of low-skill members; otherwise, it is classified as low-skill. For each household, it is also computed the share of non-employed members, capturing heterogeneity in labor-market attachment within families.

EU-SILC provides detailed information on private benefits and transfers Q_j received in each country at both the individual and household levels. At the individual level, I consider unemployment benefits, old-age pensions, survivors' benefits, disability benefits, and education-related allowances. At the household level, I include family and child allowances and housing benefits. Household tax payments are measured using EU-SILC's tax on income and social contributions variable, which captures total income taxes and

mandatory social contributions at the household level. In addition, public benefits related to education and health are imputed using country-level expenditure data from the OECD. Education spending is allocated to individuals of school age, while health expenditure is distributed across individuals using age-specific weights that increase with age, reflecting the life-cycle profile of healthcare utilization. The core outcome of interest is the household-level fiscal balance $F_{f,j}$, defined as the difference between total taxes paid and total benefits received. For household f in country j , the fiscal balance is given by

$$F_{f,j} = \tau_j(s, e)w_{i,j}(s, e) - Q_{i,j} - P_{i,j}$$

where $\tau_j(s, e)$ denotes the effective tax rate on wage $w_{i,j}(s, e)$, $Q_{i,j}$ represents the transfers and subsidies for each member of the family, and $P_{i,j}$ captures public expenditure on education and health. This construction yields a comprehensive measure of each household's net fiscal contribution, consistent with the structural framework used in the following analysis.

2.2.2 Descriptive Facts

Table 2.1 provides an overview of the EU-SILC sample used in the analysis, reporting demographic and socio-economic characteristics at both the individual and household levels for the five destination countries considered: Germany, Spain, France, Italy, and the United Kingdom.

At the population level, extra-EU migrants represent a relatively small share of the resident population, ranging from around 3 percent in Germany, France and UK, to approximately 5 percent in Spain and Italy. Despite their limited population share, extra-EU migrants display substantial heterogeneity in demographic and labor-market characteristics across countries. Migrants are slightly more likely to be female than male in most destinations with higher shares of married individuals.

Employment rates among extra-EU migrants are high overall, exceeding 80 percent in all countries and reaching over 90 percent in Germany. Skill composition, however, varies across destinations: while a majority of extra-EU migrants are classified as low-skill in Germany, Spain, France, and Italy, the United Kingdom stands out with a substantially higher share of high-skill migrants. These cross-country differences in skill composition are a central feature of the analysis and motivate the focus on migrant selection across destinations.

The lower panel of Table 2.1 reports household-level statistics, which constitute the primary unit of analysis in the paper. Consistent with individual-level patterns, migrant households account for a small fraction of total households in each country. Among migrant households, low-skill families represent the majority in Germany, France, Spain and Italy, whereas the United Kingdom again exhibits a higher share of high-skill migrant families. Native households display a more balanced skill distribution, though low-skill families remain predominant in Spain, France, and Italy.

Overall, the descriptive evidence highlights two key features of the data. First, extra-EU migrants and migrant households represent a quantitatively small but heterogeneous group across European destinations. Second, cross-country variation in skill composition and employment patterns suggests that migration outcomes differ systematically across destination countries. These differences motivate a closer examination of how migrants' and natives' fiscal contributions compare within skill groups and across countries.

Table 2.1: Proportions of Migrants and Natives - EUSILC

	DE	ES	FR	IT	UK
Population Shares	Mean	Mean	Mean	Mean	Mean
Native	0.97	0.95	0.97	0.95	0.97
Migrant Extra EU	0.03	0.05	0.03	0.05	0.03
	263,960	284,337	226,701	412,557	170,453
Migrants Extra EU Individuals					
Male	0.43	0.48	0.46	0.48	0.41
Female	0.57	0.52	0.54	0.52	0.59
Never Married	0.20	0.37	0.22	0.31	0.28
Married	0.63	0.55	0.68	0.60	0.62
Separate	0.03	0.03	0.00	0.02	0.02
Divorce	0.04	0.02	0.02	0.04	0.03
Widowed	0.10	0.03	0.07	0.03	0.05
Employed	0.91	0.82	0.82	0.82	0.79
Not Employed	0.09	0.18	0.18	0.18	0.21
High Skill	0.39	0.21	0.21	0.11	0.57
Low Skill	0.61	0.79	0.79	0.89	0.43
<i>N</i>	4,202	6,952	4,166	11,083	2,402
Household Shares					
Native Families	0.98	0.96	0.98	0.96	0.99
Migrant Extra EU Families	0.02	0.04	0.02	0.04	0.01
	152,966	134,243	123,387	213,898	94,884
Native Families					
High Skill Family	0.42	0.33	0.33	0.17	0.36
Low Skill Family	0.58	0.67	0.67	0.83	0.64
	150,460	131,087	121,400	207,738	93,543
Migrant Extra EU Families					
High Skill Family	0.38	0.20	0.16	0.10	0.61
Low Skill Family	0.62	0.80	0.84	0.90	0.39
<i>N</i>	2,506	3,156	1,987	6,160	1,341

Notes: Descriptive statistics for individuals and households drawn from the EU-SILC cross-sectional data. Population shares refer to the proportion of native and extra-EU migrant individuals in the sample. Individual characteristics for extra-EU migrants include gender, marital status, employment status, and skill level, where high skill is defined as having completed tertiary education and low skill otherwise. Employment status is based on self-reported main activity. Household shares report the proportion of native and extra-EU migrant families. A household is classified as an extra-EU migrant household if all adult household members (parents) are extra-EU migrants and no native parent is present. Skill classification at the household level is based on a majority rule: a household is classified as high skill if the number of high-skill members is greater than or equal to the number of low-skill members, and low skill otherwise. All figures are weighted sample means.

Fiscal Gaps

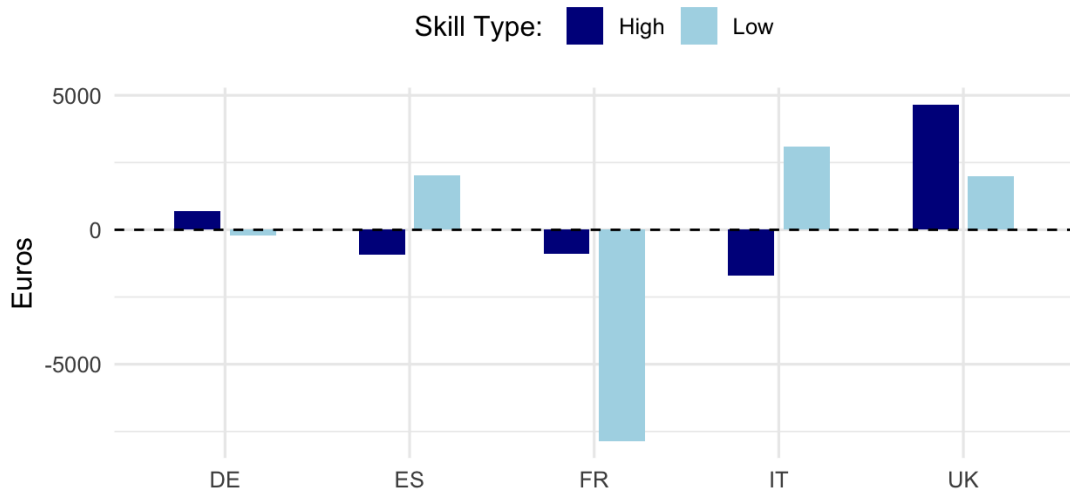
The descriptive patterns documented above motivate a closer examination of how migrants' and natives' fiscal contributions compare within skill groups and across destination countries. Economic and demographic characteristics such as wages, taxes, benefit use, and household composition, can differ systematically between migrants and natives even when they share the same skill level. These differences are largely structural, reflecting variation in average earnings, family size, and reliance on public transfers rather than differences in skill alone.

Figure 2.1 summarizes these fiscal differences by reporting, for each country, the average gap in household fiscal balance between migrants and natives of the same skill group. Fiscal balance is defined as total taxes and social contributions paid minus public and private benefits received.² Positive values indicate that migrant households contribute more than native households within the same skill category, while negative values indicate the opposite. All values are averaged over the sample period and weighted by the size of the corresponding high- and low-skill household groups in each country, providing

²Private benefits include net cash transfers received at the household level: unemployment benefits, disability benefits, sickness benefits, education-related allowances, old-age benefits, survivors' benefits, family and children-related allowances and housing allowances. Public benefits consist of imputed education and health expenditures.

a cross-sectional snapshot of fiscal gaps across destinations.

Figure 2.1: Fiscal gap between migrant and native households by skill group



Notes: $\Delta^s = \text{Fiscal Impact}_{\text{Migrants}}^s - \text{Fiscal Impact}_{\text{Natives}}^s$, $s \in \{\text{High}, \text{Low}\}$

Fiscal impact is defined as taxes and social contributions paid minus public and private benefits received. Positive values indicate higher net contributions by migrant households relative to natives within the same skill group. Values are averaged over the sample period and weighted by group size.

The figure reveals substantial heterogeneity across countries and skill groups. From a conceptual standpoint, one would generally expect native households to exhibit more favorable fiscal contributions than migrant households within the same skill group, reflecting higher average earnings, longer labor-market attachment, and lower reliance on public transfers. Likewise, higher-skilled households are expected to contribute more than their low-skill counterparts.

The patterns in the figure only partially align with these expectations. In the United Kingdom, high-skill migrant households contribute substantially more than high-skill native households on average, a result that contrasts with the baseline expectation but is consistent with existing evidence documenting a positive fiscal contribution of migrants in the UK context (Dustmann and Frattini, 2014b). By contrast, low-skill migrant households in France exhibit a markedly negative fiscal gap relative to natives, echoing findings in the literature pointing to more limited or negative fiscal contributions of migrants in the French case (Chojnicki and Ragot, 2016). In other countries, both the sign and magnitude of the fiscal gap vary across skill groups, indicating that there is no uniform relationship between migrant status, skill level, and fiscal contribution. Overall, these patterns suggest that fiscal gaps are shaped by destination-specific economic and institutional conditions rather than by skill composition alone.

To better understand the origins of these fiscal gaps, Table 2.2 compares average economic and demographic characteristics of migrant and native households across countries. Several consistent patterns emerge.

First, migrants earn lower average labor income than natives within the same skill group in all five countries. This wage gap directly translates into lower personal income taxes and social security contributions. As a result, differences in fiscal contributions arise already on the revenue side, even before accounting for benefit receipt. Lower earnings thus constitute a key starting point for understanding why migrants' net fiscal balances may differ from those of natives with comparable skills. The United Kingdom is the only exception, where migrant households display higher net income relative to other

countries. This reflects the fact that migrant and native wages are broadly similar in the UK.

Second, consistent with lower incomes, migrant households pay less in total taxes and social contributions than native households. This pattern is remarkably stable and highlights that fiscal gaps are not driven solely by differences in public expenditure but also reflect lower revenue generation by migrant households.

Third, on the expenditure side, migrant households receive lower public benefits than native households on average. Since public benefits in this analysis consist of imputed education and health expenditures, this pattern is consistent with migrants' younger age profiles and, in several countries, slightly smaller household size, both of which reduce assigned in-kind spending. Differences in inactivity rates between migrants and natives are modest, suggesting that variation in public benefits is driven primarily by demographic composition rather than labor-market detachment.

Finally, demographic characteristics help further contextualize these fiscal patterns. Migrant households are on average younger and slightly smaller than native households, while exhibiting inactivity rates that are broadly similar or marginally higher. Younger household age implies that migrants are often earlier in their earnings life cycle, with fiscal contributions that may evolve over time. At the same time, migrant households receive lower amounts of private benefits, such as unemployment and sickness benefits, consistent with differences in employment histories, eligibility conditions, and potentially informational barriers affecting benefit take-up.

Taken together, these economic and demographic differences explain a substantial share of the variation observed in migrants' and natives' fiscal contributions within the same skill group. Migrants generally earn lower wages and pay less in taxes, receive slightly more public benefits, and differ systematically in household composition relative to natives. Importantly, the magnitude and direction of these fiscal gaps vary across countries, indicating that there is no one-size-fits-all pattern.

Because these fiscal differences depend on the relative contribution of high- and low-skill households, a next step is to examine how the skill composition of migrant populations differs across destinations and over time. Understanding how the shares of high- and low-skill migrants evolve helps clarify whether cross-country fiscal patterns reflect as well differences in who migrates rather than only differences in fiscal behavior within skill groups.

Table 2.2: Economic and Demographic Characteristics of Households - EUSILC

	DE		ES		FR		IT		UK	
	N	M	N	M	N	M	N	M	N	M
Net Income	36092.33	25803.73	21115.17	15247.79	29641.69	12915.14	23657.87	18012.69	26893.18	30270.74
Private Benefits Net	9441.82	2817.19	8892.73	1960.36	14113.05	7697.39	11402.89	1854.96	10792.45	4440.99
Public Benefits	7529.25	4343.84	5028.24	3903.42	7124.73	4638.30	5494.25	3299.83	6224.27	4238.22
All Taxes Paid	15459.22	14107.79	6158.00	2116.74	11303.17	3745.94	12444.62	4791.71	11193.81	11331.07
Family Size	2.04	1.61	2.55	2.49	2.15	1.70	2.47	1.83	2.16	2.02
Inactive Share	0.06	0.10	0.14	0.15	0.09	0.21	0.16	0.12	0.07	0.18
Family Age	49.94	35.47	49.47	36.25	49.55	34.42	51.43	38.33	50.66	34.88
N	150,460	2,506	131,087	3,156	121,400	1,987	207,738	6,160	93,543	1,341

Notes: The table reports average household-level characteristics for native (N) and extra-EU migrant (M) households by country. All monetary variables are expressed in euros and adjusted for inflation using the Consumer Price Index (CPI) from Eurostat. Net income refers to total household labor income net of taxes and social contributions. Private benefits are defined as the sum of net cash transfers received at the household level, including unemployment benefits, disability benefits, sickness benefits, education-related allowances, old-age benefits, survivors' benefits, family and children-related allowances, and housing allowances. Public benefits capture imputed education and health expenditures from OECD. All taxes paid include income taxes and social contributions and wealth taxes. Family size denotes the number of household members, while the inactive share is the proportion of household members not in employment. Family age refers to the average age of household members.

Skill Composition Overtime

Figure 2.2 reports the evolution of the skill composition of native and migrant households across destination countries between 2011 and 2018 from EU-SILC. For ease of comparison, the series are normalized to one in the base year (2011), so that values represent changes relative to the initial composition rather than levels. The figure distinguishes between high- and low-skill households and reports separate trends for natives and migrants.

Two patterns emerge clearly. First, the skill composition of native households remains remarkably stable over time across all five countries. Both the shares of high-skill and low-skill native households exhibit only modest fluctuations around their initial levels, suggesting that changes in the native population's skill distribution are gradual and driven by slow-moving forces such as educational attainment and demographic transitions.

By contrast, the skill composition of migrant households displays substantial variation over time and across destinations. In several countries, the relative shares of high- and low-skill migrants experience pronounced increases and declines over short horizons, with markedly different trajectories across countries. These fluctuations stand in sharp contrast to the stability observed among natives and point to migration-specific forces shaping the composition of migrant inflows.

The differential dynamics between natives and migrants suggest that changes in migrant skill composition are unlikely to be driven by common macroeconomic trends alone. Instead, they are consistent with the presence of destination-specific factors that affect who migrates and when. In particular, immigration and labor-market policies related to it can alter the relative costs and returns to migration for different skill groups, providing an explanation for the observed ups and downs in migrant skill shares across countries and over time.

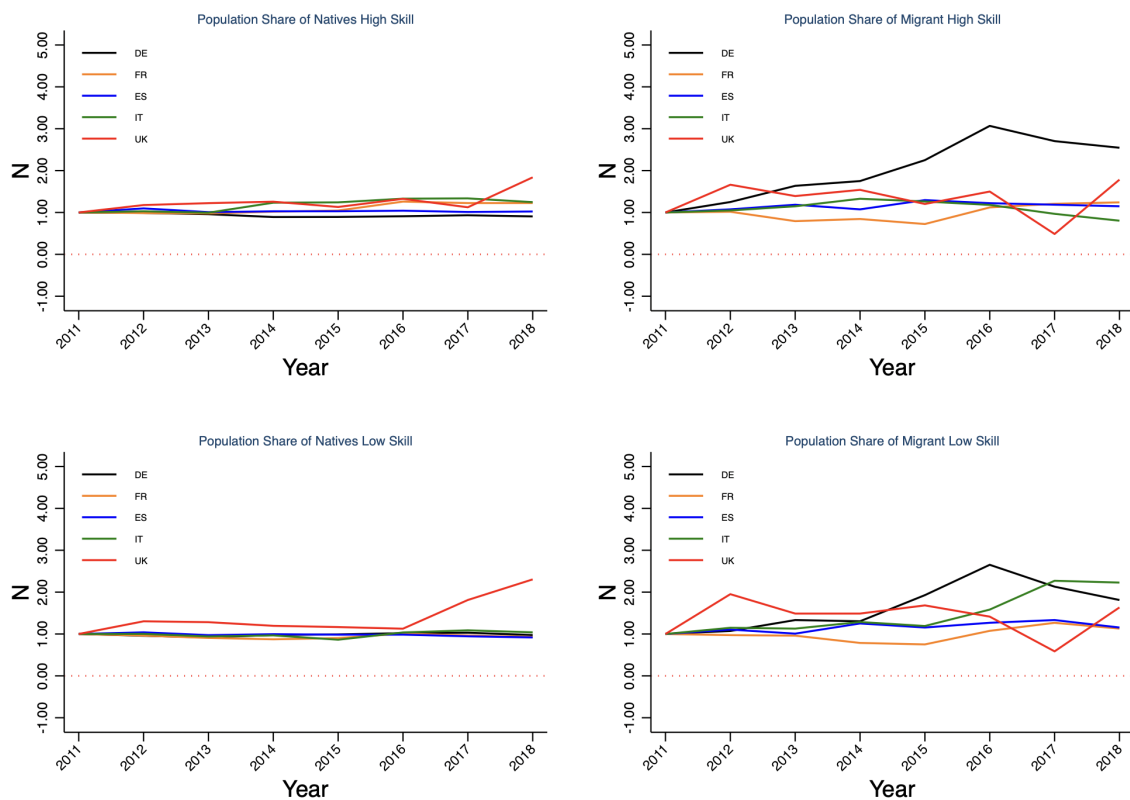
To shed light on this interpretation, I draw on information from the Labour Market Reform Database (LABREF), which documents labor market and welfare policy measures enacted by European countries, including reforms affecting labor mobility and immigration. Reading the evolution of migrant skill composition alongside the timing and scope of these policy measures suggests that periods of pronounced changes in the relative shares of high- and low-skill migrants often coincide with shifts in policy design that differentially affect skill groups. While this evidence is descriptive, it is directly consistent with the central mechanism analyzed in this paper, namely that immigration policy shapes migrant self-selection and, through that channel, fiscal outcomes across destinations.

Selected country episodes provide further qualitative context for the patterns observed in the data. In Germany, the gradual increase in both high- and low-skill migrant households from 2012 onward occurs during a period characterized by a sequence of reforms aimed at expanding labor market access for third-country nationals, including measures targeting skilled migration as well as broader initiatives facilitating entry, training, and employment for asylum seekers and other migrants. After 2016, the stabilization and slight decline in migrant shares coincides with a shift in policy emphasis toward integration and permanence rather than further expansion of inflows ³. In contrast, France

³Gesetz zur Umsetzung der Hochqualifizierten-Richtlinie der Europäischen Union (HQRLUmsG) EIRO 2012; Reorganisation of the Ordinance on the Admission of Foreigners for the Purpose of Taking up Employment (Beschäftigungsverordnung) NRP 2013; Freedom of movement of workers with transitional provisions in the first phase in force since 1 July 2013 NRP; Verordnung über die Beschäftigung von Ausländerinnen und Ausländern (Beschäftigungsverordnung BeschV) vom 6. Juni 2013 (BGBl. I S. 1499) EEO; Gesetz zur Verbesserung der Rechtsstellung von asylsuchenden und geduldeten Ausländern vom 23. Dezember 2014 EEPO Report; Gesetz zur Änderung des Zwölften Buches Sozialgesetzbuch und weiterer Vorschriften, Bundesgesetzblatt 2015 I 2557 EEPO; 29 July 2015 Amendment of the Em-

and Spain display relatively stable migrant skill shares throughout the period, consistent with a policy environment marked by fewer immigration reforms explicitly altering access across skill groups. Italy shows a gradual increase in the share of low-skill migrant households starting around 2013, a period that overlaps with reforms simplifying work-contract procedures for third-country nationals ⁴. The United Kingdom stands out for a pronounced break around 2016, when both high- and low-skill migrant shares decline, followed by a partial recovery in subsequent years, a pattern that aligns with broader evidence of a post-Brexit reorientation of migration flows away from EU and toward non-EU migrants (Portes (2022)). While these observations are descriptive, they illustrate how changes in migrant skill composition often unfold alongside shifts in immigration and labor-market policy environments, motivating the explicit role assigned to immigration policy in shaping migrant self-selection in the structural framework developed in the next section.

Figure 2.2: Skill Composition of Families by Nativity and Skill



Notes: Evolution of the skill composition of native and extra-EU migrant families across five destination countries between 2011 and 2018. For each panel, values are normalized to one in the base year (2011), so that the vertical axis captures relative changes over time rather than levels. The top panels report the population share of high-skill native and migrant families, while the bottom panels report the corresponding shares for low-skill families. Skill status is defined at the household level, with a household classified as high-skill if the number of high-skill members is greater than or equal to the number of low-skill members. Native and migrant populations are plotted separately to highlight differences in dynamics. While the skill composition of native families remains relatively stable over time, migrant skill shares exhibit pronounced cross-country and temporal variation, suggesting the influence of destination-specific factors rather than common macroeconomic trends.

ployment Ordinance (Beschäftigungsverordnung) ELLN; “Integration Law” (“Integrationsgesetz”) ESPN; Integrationsgesetz 2017/2018 NRP

⁴DL 76/2013 NRP

2.3 Theoretical Analysis

The theoretical section of the analysis presents a model that conceptualizes the interplay between immigration policy and individual self-selection, and how these collectively influence the fiscal impact on host countries.

The theoretical model which fits well this type of framework is the Roy Model which can be used to analyze migration decisions. In the setting of this project, migration decision is driven by immigration policy and self-selection which will in turn impact the fiscal system of the destination country.

Hence, migration decision is modeled through two forces. The first is the immigration policy in place, defined by the mobility cost imposed by the destination country, which every potential household must bear to relocate. The model assumes uniform tax rates and distribution of public goods across different types of households, making mobility cost the key differentiator.

The second one is self-selection for the type of household (high or low skill): a household's decision to migrate is also influenced by its skill level. high-skill households may prioritize countries offering greater returns in the labor market or a larger share of public goods, while low-skill households might make decisions based on different criteria.

These dynamics are integrated into a theoretical framework that considers the characteristics of individuals and the specifics of immigration policy, with the fiscal impact in the destination country as the ultimate effect.

Geography and Agents

The framework considers a world divided into J distinct countries, each with unique immigration policies, public goods provisions, wage structures, and labor markets: $j \in J$ denotes destination countries and $o \in J$ denotes the origin countries. When $o = j$ there is no migration, individuals stay in their origin country.

The world is inhabited by an exogenous measure $\bar{I}$ of infinitely lived individuals distinguished exogenously in skill categories s and employment categories e . For skill categories s , there are high skilled $s = 1$ and low skilled $s = 0$. For employment categories e , there are employed individuals $e = 1$ and non-employed individuals $e = 0$ (e.g. children, old parents). The initial distribution of agents across countries is assumed to be exogenous. The categories of skills s and employment e are included in the definition of each individual $i \in \bar{I}$ and specified when needed.

Individuals categorized in skill level and by employment status form families. A family f is categorized into high or low skill category s depending on its components N_f : if the majority is high skilled $s = 1$ then the family is categorized as a high skilled family. Hence, each family is formed by: high or low skilled employed-individuals $e = 1$, working and taking the decision to migrate; and the non-employed individuals $e = 0$ which follow the employed part of the family in the destination country chosen.

Migration decisions within this theoretical model are made collectively by families based on the aggregate skill level of the household. Hence, given an origin o , each family chooses a destination j considering the immigration policy in place in the destination country j . The immigration policy is represented by the distribution of mobility cost $\mu_j(s)$ which the family has to pay to the destination country j according to the family skilled aggregated category s . The mobility cost impacts the family's migration decision in the following ways: if $j = o$ and there is no migration, then there will be no mobility cost to pay (i.e. $\mu_j(s) = 0$); if $j \neq o$ and there is migration to another country then there will be the mobility cost to sustain (i.e. $\mu_j(s) \neq 0$).

This decision-making process endogenously assigns each family to either remain in the

origin country or migrate to an alternative destination, based on comparisons of expected utility across locations. Immigration policy affects this choice by entering the migration decision through skill-specific mobility costs, $\mu_j(s)$, which shift the relative attractiveness of destinations for different family types. Policies that are broadly open or inclusive are characterized by lower mobility costs across skill groups, facilitating migration for both high- and low-skill families. In contrast, selective immigration policies aimed at attracting high-skill labor operate by reducing mobility costs for high-skill families while raising them for low-skill families, thereby discouraging the latter from migrating.

Through this mechanism, immigration policy shapes migrant self-selection across destinations. By altering the relative attractiveness of countries for different skill types, policy affects the probabilities with which high- and low-skill families choose each destination. Since families differ systematically in their expected fiscal contributions, these selection effects translate into differences in aggregate fiscal outcomes across countries.

Preferences of a unitary family are represented by a utility function defined over family consumption in location j , $C_{f,j}$, and an unobserved preference component specific to family f and location j , $v_{f,j}$. The term $v_{f,j}$ captures idiosyncratic factors affecting location choice that are not explicitly modeled and is assumed to follow a logistic distribution. Hence, the utility function of family f from residing in location j is expressed as:

$$U_{f,j} = C_{f,j} + v_{f,j} \quad (2.1)$$

The budget constraint of the family is:

$$C_{f,j} = \sum_{i \in N_f} c_{i,j} = \sum_{i \in N_f} [w_{i,j} (1 - \tau_{i,j}) + Q_{i,j} + P_{i,j} - \mu_{s,j}] \quad (2.2)$$

Where $w_{i,j}$ is the real wage of country j for individual i multiplied and adjusted by the tax rate $\tau_{i,j}(s, e)$. In particular:

$$w_{ij} = \begin{cases} w_{i,j}(0, 1) & \text{if low skill } s = 0 \\ w_{i,j}(1, 1) & \text{if high skill } s = 1 \end{cases} \quad (2.3)$$

The term $Q_{i,j}$ captures cash-based transfers and subsidies received by individual i in destination country j , such as unemployment, sickness, disability, and other cash benefits. These transfers depend on individual characteristics, including skill level s and employment status e . The parameter $\mu_j(s)$ represents skill-specific mobility costs associated with destination j and captures the role of immigration policy in shaping migration incentives: higher values of $\mu_j(s)$ increase the cost of migrating to country j for families of skill type s , thereby reducing its attractiveness, while lower values facilitate migration. Finally, $P_{i,j}$ denotes public goods provided in country j , which depend on individual characteristics, such as age, and consist of education and health services.

The model normalizes the price of consumption to unity. As a result, the budget constraint is incorporated directly into the utility function by expressing consumption in terms of real income, yielding the final utility equation:

$$U_{f,j} = \beta_s^1 \sum_{i \in N_f} w_{i,j} (1 - \tau_j) + \beta_s^2 \sum_{i \in N_f} Q_{i,j} + \beta_s^3 \sum_{i \in N_f} P_{i,j} - \beta_s^4 \mu_j(s) + v_{f,j}. \quad (2.4)$$

Where, at the country level:

- $Q_j = \sum_{i \in N_j} Q_{i,j}$
- $P_j = \sum_{i \in N_j} P_{i,j}$

Production

The production process is managed by a representative firm in each country j , utilizing

labor E_j and technology A_j as inputs. The production function is characterized by a Constant Elasticity of Substitution (CES) form, which allows for different degrees of substitutability ρ between labor and technology. This CES production function can be represented as:

$$Y_j = [\gamma_0 (E_{0,j})^\rho + \gamma_1 (E_{1,j})^\rho]^{\frac{1}{\rho}} A_j \quad (2.5)$$

Government

In this setting, the government's role is to generate public goods through the taxes collected from the working population. The total tax revenue, denoted by T_j , in any given country j is a function of the wages earned by workers ($w_{i,j}(s, e)$) and the tax rate ($\tau_{i,j}(s, e)$) set by the government according to the local tax policies and the skill categories (which influences the wage) of the individual. The tax revenue equation can be represented as:

$$T_j = \sum_{i=1}^{N_j} \tau_{i,j}(s, e) w_{i,j}(s, e) \quad (2.6)$$

where N_j is the set of all individuals in country j .

Public spending in country j , denoted by G_j , is allocated across two broad components. The first consists of public goods, P_j , such as education and health services, which are provided to individuals according to demographic characteristics and are non-rival in consumption. The second component includes cash-based public transfers and subsidies, Q_j , which comprise social benefits and transfer payments linked to individuals' employment status and eligibility. Together, these two components determine the government's expenditure side and enter households' budget constraints and utility through the channels described above. The government's budget constraint for public goods provision in country j is then:

$$G_j = Q_j + P_j = T_j \quad (2.7)$$

The government budget constraint requires that total public expenditure in country j , consisting of cash transfers Q_j and in-kind public goods P_j , is fully financed by tax revenues T_j collected from the working population. This balanced-budget condition closes the public sector in the model and links individual labor-market outcomes directly to the provision of public goods and transfers.

The composition of public spending between transfers and in-kind goods reflects government policy choices and institutional design. These choices affect households' disposable resources and utility and therefore influence the relative attractiveness of destinations for different family types. For instance, a country with a more generous system of cash transfers may be relatively more attractive to households with weaker labor-market attachment, while higher investment in education and health services may appeal to families valuing access to public goods.

Public transfers and in-kind public goods are assigned at the individual level based on observable characteristics such as skill, employment status, and age, as described above. Through this channel, fiscal policy interacts with household composition to shape both individual welfare and aggregate fiscal outcomes, providing a key link between immigration policy, migrant self-selection, and the fiscal impact of migration.

Fiscal Impact

Fiscal impact is the key outcome variable of the analysis and summarizes the net contribution of households to public finances in each country. It captures the interaction between labor-market outcomes and household composition. For each family f residing

in country j , fiscal impact is defined as the sum of individual-level fiscal balances across household members and is computed as follows:

$$F_{f,j} = \sum_{i \in N_f} F_{i,j} = \tau_{i,j} w_{i,j} - Q_{i,j} - P_{i,j} \quad (2.8)$$

In this expression, fiscal impact reflects taxes and social contributions paid by employed household members, net of cash-based public transfers $Q_{i,j}$ and in-kind public goods $P_{i,j}$ received by each individual. Cash transfers depend on employment status and eligibility, while in-kind public goods consist of education and health services assigned on the basis of demographic characteristics such as age. A positive value of $F_{f,j}$ indicates that a household contributes more in taxes than it receives in benefits, whereas a negative value implies a net fiscal cost.

Immigration policy affects fiscal impact indirectly by shaping migrant self-selection. Through the skill-specific mobility cost $\mu_j(s)$, policy alters the composition of families choosing to locate in each country. Since families differ systematically in earnings potential, benefit receipt, and demographic structure, changes in migrant composition translate into differences in aggregate fiscal outcomes. In this sense, fiscal impact serves as the link between immigration policy, household selection, and public finances within the structural framework of the model.

Migration Decision

The migration decision is taken at the family level and is based on a comparison of expected utility across locations. Families evaluate alternative destinations by weighing differences in labor-market outcomes, tax schedules, public transfers, in-kind public goods, and mobility costs relative to their current country of residence. Through this choice, families endogenously sort across countries, shaping the distribution of high- and low-skill households and, in turn, aggregate fiscal outcomes.

Formally, family f chooses to migrate from its origin country o to destination country j whenever the utility associated with residing in j exceeds that of remaining in o . That is, family f migrates to country j if:

$$U_{f,j} > U_{f,o} \quad (2.9)$$

2.3.1 Solving the Model

Solving the model requires characterizing households' location choices and the resulting allocation of labor across countries, together with the associated fiscal variables, and then defining the equilibrium conditions that jointly determine these outcomes.

Demand:

Recalling the production function (2.5), we define the profits of the representative firm as revenues minus expenses:

$$\Pi_j = Y_j - w_{1,j} E_{1,j} - w_{0,j} E_{0,j} \quad (2.10)$$

Taking the first order conditions with respect to $E_{1,j}$ and $E_{0,j}$ we get the ratio characterizing the demand:

$$\frac{w_{1,j}}{w_{0,j}} = \frac{\gamma_1}{\gamma_0} \left(\frac{E_{1,j}^d}{E_{0,j}^d} \right)^{\rho-1} \quad (2.11)$$

Where:

$$E_j^d = E_{1,j}^d + E_{0,j}^d \quad (2.12)$$

It's the total workforce available in country j .

This equation defines the demand side of the labor market in each country, balancing the relative demand for different skill levels of labor with the corresponding wage rates.

Supply:

On the supply side, the model focuses on families' migration decisions, distinguishing between high-skill and low-skill households. Supply is characterized by the probability that a family of skill type s chooses destination country j , conditional on its current country of residence o . These choice probabilities summarize how wages, taxes, cash transfers, in-kind public goods, and skill-specific mobility terms jointly determine the allocation of households across countries.

$$\sum_o \Pr(j \mid 0, o) = \frac{\Pr(j) \cap \Pr(0, o)}{\Pr(0, o)} = E_{0,j}^s \quad (2.13)$$

$$\sum_o \Pr(j \mid 1, o) = \frac{\Pr(j) \cap \Pr(1, o)}{\Pr(1, o)} = E_{1,j}^s \quad (2.14)$$

Equation (2.13) and (2.14) defines the expected supply of low-skill ($s = 0$) and high-skill ($s = 1$) families in country j , aggregating migration choices across all countries.

Families choose their location by comparing expected utility across all feasible destinations. Under the assumption that the idiosyncratic preference shocks $v_{f,j}$ follow a Type I extreme value distribution, the probability that family f chooses destination j takes the standard multinomial logit form:

$$P_{f,j} = \frac{\exp(C_{f,j})}{\sum_d \exp(C_{f,d})}, \quad (2.15)$$

where $C_{f,j}$ denotes the deterministic component of family utility in country j , and the denominator sums over all potential locations d , including the current country of residence.

These choice probabilities determine how immigration policy through its effect on wages, taxes, transfers, public goods, and mobility terms shapes migrant self-selection across destinations. By influencing the composition of high- and low-skill households across countries, the supply side of migration plays a central role in determining aggregate fiscal outcomes.

The derivation of the multinomial logit choice probabilities is standard and is provided in Appendix 2.A.1.

2.3.2 Equilibrium

Definition 1:

Given country-specific fiscal and policy parameters $\{\tau_{j,t}, Q_{j,t}, P_{j,t}, \mu_{j,t}(s)\}$, an equilibrium at time t is a set of skill-specific wages $\{w_{0,j,t}, w_{1,j,t}\}_{j \in J}$ and an allocation of families across countries such that all agents optimize and all markets clear.

In equilibrium, firms choose labor demand to maximize profits, taking wages as given, and optimal labor demand for each skill type satisfies the first-order conditions derived from the production problem (see Equation (2.10)). Families choose their country of residence by comparing expected utility across all feasible locations. For any current country o and destination j , the probability that family f chooses j is given by:

$$\Pr(j \mid f, o) = \Pr(U_{j,f,o} \geq U_{-j,f,o}) \quad \forall j, f \quad (2.16)$$

where $U_{f,j}$ depends on wages, taxes, transfers, in-kind public goods, and skill-specific mobility terms.

Labor markets clear in each country and for each skill group, so that expected labor supply equals labor demand:

$$E_{s,j}^s = E_{s,j}^d \quad s \in (0, 1). \quad (2.17)$$

Expected labor supply is determined by families' migration choices and the resulting distribution of households across destinations.

The goods market clears in each country, with total output equal to aggregate consumption,

$$Y_{j,t} = C_{j,t}. \quad (2.18)$$

Finally, the government budget balances in every country:

$$T_{j,t} = G_{j,t}, \quad (2.19)$$

where public expenditure $G_{j,t}$ includes both cash transfers $Q_{j,t}$ and in-kind public goods $P_{j,t}$.

Equilibrium migration choices jointly determine the skill composition of resident households, employment outcomes, and fiscal balances across destinations. Immigration policy affects equilibrium outcomes indirectly by shaping migrant self-selection through skill-specific mobility terms, which alter the relative attractiveness of destinations for different family types.

2.4 Quantitative Analysis

2.4.1 Estimation

The analysis continues with a conditional multinomial logit framework that models families' location choices across a set of alternative destinations. This approach is well suited to studying migration decisions in which each household chooses among multiple countries (i.e. Germany, France, Italy, Spain, and the United Kingdom) based on destination-specific economic and fiscal attributes.

To implement this framework, the dataset is reshaped into a choice-based longitudinal format. Each household is replicated once for each potential destination country, generating a set of alternative location options for every family. The dependent variable indicates whether a given country corresponds to the household's observed location, while the remaining alternatives represent feasible but unrealized choices. This structure mirrors the choice problem faced by families when evaluating migration opportunities.

Key explanatory variables, including potential wages, taxes, private transfers, and public benefits, are constructed at the household level for each destination. Since these variables are not directly observed for non-chosen locations, they are proxied using destination-specific averages computed over rolling time windows. In particular, for each country, skill group, and household type, fiscal and labor-market variables are averaged over a three-year period. This approach smooths short-run fluctuations and provides a more stable measure of the economic conditions that families are likely to anticipate when considering relocation.

The use of time-averaged potential outcomes reflects the idea that migration decisions are based on expectations about medium-run economic conditions rather than transitory shocks. Moreover, all potential outcomes are allowed to differ by skill type, capturing the fact that high-skill and low-skill families face systematically different wage structures, tax liabilities, and benefit eligibility across countries.

To focus on migration decisions that are most plausibly linked to contemporaneous economic conditions and policy environments, the estimation sample is further restricted to first-generation migrant households with a clearly identified timing of arrival. Specifically, for migrant families, I identify both the earliest and the most recent year of arrival among household members and retain only households whose oldest member arrived five years prior to the observation year. This restriction ensures that migration choices are recent enough to be meaningfully related to the fiscal and labor-market conditions used to construct potential outcomes, while excluding long-settled households for which location choices may reflect past policy regimes or assimilation dynamics.

This conditional multinomial logit estimation provides reduced-form evidence on how economic incentives and fiscal conditions shape families' location choices. While not causal in itself, this step serves two important purposes. First, it offers an empirical benchmark for the direction and relative importance of different fiscal and labor-market variables. Second, it informs the structural analysis that follows by guiding parameter calibration and validating the key mechanisms embedded in the theoretical model. In this sense, the conditional logit results act as a bridge between the descriptive evidence and the structural framework used to quantify the fiscal impact of immigration policy through migrant self-selection. The estimates are reported in Table 2.3.

Potential net wages positively affect destination choice for high-skill families, confirming that expected earnings are a primary determinant of migration decisions for this group. This result is consistent with the evidence in [Grogger and Hanson \(2011b\)](#), who document strong wage responsiveness among high-skill migrants. In contrast, the estimated wage coefficient for low-skill families is negative. This suggests that higher expected wages at destination do not necessarily translate into higher utility for low-skill households once other destination attributes are taken into account.

Potential private benefits enter positively for high-skill families, indicating that destinations offering greater opportunities for private consumption and market-based benefits are more attractive to this group. For low-skill families, the coefficient on private benefits is close to zero, suggesting a limited role in shaping their location choices. This pattern presents the idea that transfers opportunities matter more for households with higher earning potential, while low-skill households place less weight on these margins.

Public benefits for high-skill families present a negative coefficient, indicating that more generous public benefit systems reduce destination attractiveness. This is consistent with an interpretation in which high-skill households associate generous public provision with higher taxes or redistribution. For low-skill families, public benefits have a positive effect, confirming that welfare generosity acts as a pull factor for this group. This result aligns with the welfare-magnet hypothesis documented in [De Giorgi and Pellizzari \(2009\)](#) and with broader evidence that low-skill migrants are more responsive to redistributive policies than to labor-market incentives.

The estimated destination-specific migration cost parameters reveal substantial heterogeneity across countries and skill groups. Relative to Italy (the reference country), Germany and France are associated with higher migration costs for both skill types, particularly for low-skill families. The United Kingdom exhibits a positive attractiveness for high-skill families but remains unattractive for low-skill households, while Spain emerges as relatively more attractive for high-skill migrants and less so for low-skill ones.

Taken together, these results highlight a clear pattern of skill-specific self-selection: high-skill families respond primarily to wage incentives and are discouraged by redistributive public policies, while low-skill families are drawn to destinations offering more generous public benefits and are less responsive to wage differentials. These estimates provide reduced-form evidence that guides the calibration of migration costs and preference

parameters in the structural model.

Table 2.3: Conditional Multinomial Logit Estimates

	High-Skilled (1)	Low-Skilled (2)
<i>Utility Parameters</i>		
β^1 (Net Wages)	0.0097 (0.0085)	-0.0334 (0.0056)
β^2 (Private Benefits)	0.0566 (0.0154)	0.0001 (0.0151)
β^3 (Public Benefits)	-0.0345 (0.0456)	0.0349 (0.0243)
<i>Migration Costs (μ_j)</i>		
Germany	-1.511 (0.300)	-2.857 (0.374)
Spain	0.095 (0.124)	-1.117 (0.138)
France	-0.811 (0.181)	-1.564 (0.226)
Italy – Reference Country	0	0
United Kingdom	0.220 (0.176)	-2.678 (0.221)
<i>Standard Deviations</i>		
σ_μ	0.741	1.176
<i>Model Specification</i>		
ρ (CES parameter)		0.5
σ (Elasticity of substitution)		2.0

Notes: This table reports estimates from a conditional multinomial logit model of household location choice across five European destinations, estimated separately for high-skill and low-skill families. Coefficients reflect the marginal utility of destination-specific attributes relative to Italy, which is the reference country. For low-skill families, reported coefficients incorporate the relevant skill-specific interactions and therefore represent the total marginal effect of each variable on location choice. Country fixed effects μ_j capture migration costs. Standard deviations σ_μ^{HS} and σ_μ^{LS} are used to discipline the magnitude of policy shocks to migration costs in the counterfactual simulations. The CES production parameter ρ and the elasticity of substitution σ are imposed from the structural model and are not estimated in this stage. Standard errors are reported in parentheses.

To translate these self-selection patterns into general-equilibrium outcomes, the model requires information on how changes in skill composition map into wages and output across destinations. Table 2.4 reports the country-specific CES production function parameters used for this purpose. The estimated production weights exhibit substantial cross-country heterogeneity in the relative importance of high-skill and low-skill labor. Spain and France display the strongest reliance on high-skill labor, with high ratios of high to low-skill weights (γ_1/γ_0 equal to 1.63 and 1.37, respectively), while Germany and the United Kingdom also favor high-skill labor, although less sharply. Italy stands out as the only country in which the weight on low-skill labor exceeds that on high-skill labor ($\gamma_1/\gamma_0 < 1$).

This heterogeneity plays a central role in the model’s transmission mechanism. While the conditional logit captures how migration policy and economic incentives shape who moves where, the production parameters determine how those movements affect wages, output, and fiscal outcomes once equilibrium adjustments take place. In countries with a strong bias toward high-skill labor, changes in the availability of skilled workers translate into large marginal productivity and wage responses, whereas in Italy similar compositional shifts generate different effects. By combining skill-specific migration responses with country-specific production structures, the model links immigration policy to endogenous self-selection and, ultimately, to heterogeneous fiscal impacts across destinations. This framework provides the foundation for the counterfactual analysis that follows, allowing to evaluate how alternative immigration policies reshape migration patterns, wages, pro-

duction, and public finances through general-equilibrium adjustments.

Table 2.4: Production Function Parameters by Country

	Germany	Spain	France	Italy	United Kingdom
<i>CES Production Weights</i>					
γ_0 (Low-skilled)	135.37	93.59	133.72	114.31	128.17
γ_1 (High-skilled)	157.63	152.37	183.33	95.61	185.80
<i>Derived Measures</i>					
γ_1/γ_0	1.16	1.63	1.37	0.84	1.45

Notes: This table reports country-specific parameters of the CES production function used in the structural model. The parameters γ_0 and γ_1 denote the production weights on low-skill and high-skill labor and govern the contribution of each skill type to aggregate output. The ratio γ_1/γ_0 summarizes the relative importance of high-skill versus low-skill labor in production and provides a simple measure of skill bias across countries.

2.4.2 Counterfactual Results

This section presents a set of counterfactual policy experiments designed to quantify how immigration policy shapes migrant self-selection and fiscal outcomes in destination countries. The core mechanism is the interaction between immigration policy and endogenous migrant sorting: policy reforms alter the relative attractiveness of destinations by skill group, which changes the composition of migrant inflows and generates general equilibrium adjustments in wages, production, and public finances.

While the model allows for a wide range of counterfactuals, the discussion focuses on five representative scenarios that capture some main policy margins to understand the working of the model: Germany opening to low-skill workers to address labor shortages; Italy and Spain jointly opening to low-skill migration in response to population aging; France attracting both high and low-skill workers; Italy attracting high-skill migrants and lastly a coordinated opening to low-skill migration in Germany, France, and the United Kingdom.

Germany Opens to Low-Skill Immigrants

Figure 2.3 reports the general equilibrium effects of a policy reform in which Germany substantially reduces entry barriers for low-skill workers, while keeping high-skill migration policies unchanged. By altering relative mobility incentives, the reform induces strong self-selection of low-skill households toward Germany.

As shown in Figure 2.3 (top-left panel), Germany experiences a large increase in the low-skill labor share, accompanied by a decline in the high-skill share. The remaining destinations (e.g. Spain, France, Italy, United Kingdom) exhibit the mirror pattern, reflecting the reallocation of migrant flows across countries following the policy change.

These compositional shifts translate into wage adjustments (Figure 2.3, top-right panel). In Germany, the inflow of low-skill workers depresses low-skill wages, while high-skill wages increase due to relative scarcity. In the other destinations, high-skill wages decline as skilled workers relocate from Germany, whereas low-skill wages rise as reduced competition improves their labor-market position.

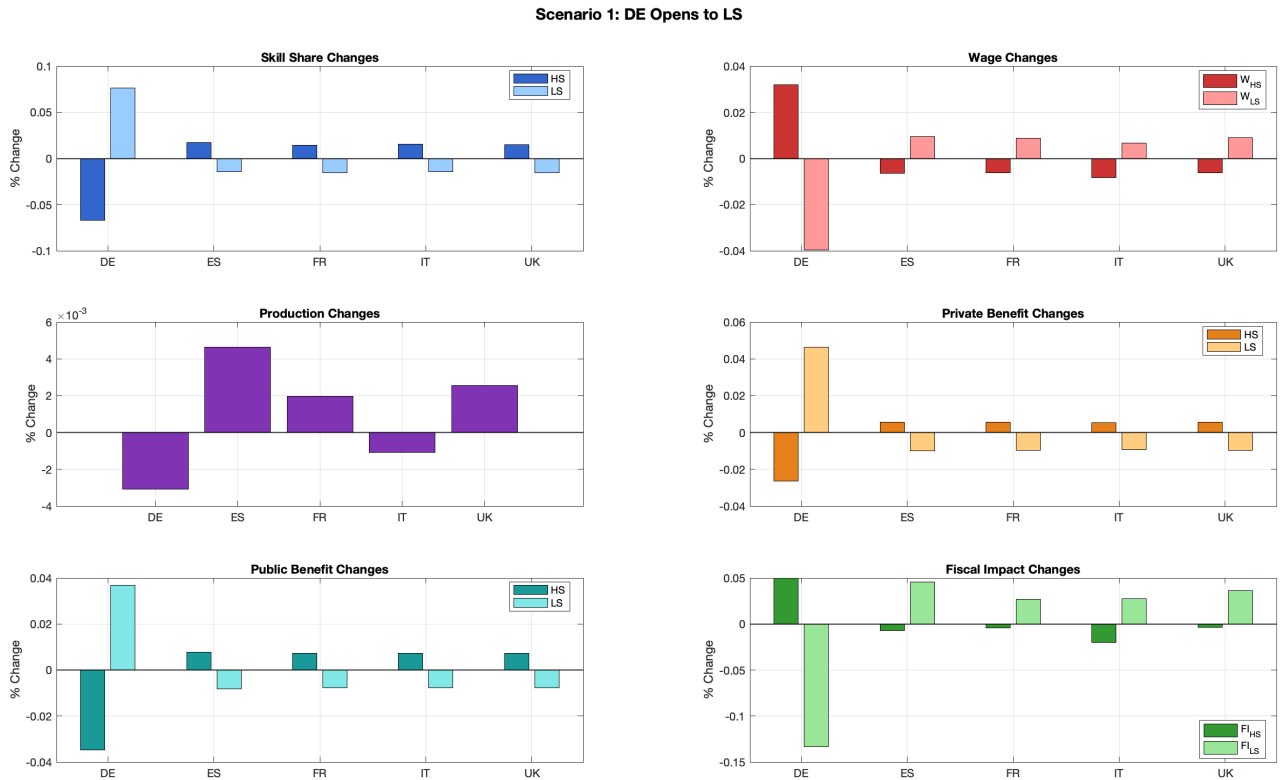
Aggregate production responses are heterogeneous (Figure 2.3, middle-left panel). Germany's output declines as the workforce becomes less skill-intensive. Spain, France, and the United Kingdom experience production gains driven by increased high-skill employment. Italy, by contrast, exhibits a modest production decline despite receiving skilled workers, reflecting its production structure in which low-skill labor carries relatively greater weight.

Private and public benefit utilization adjusts endogenously with wages and household composition (Figure 2.3, middle-right and bottom-left panels). Private benefit consumption declines for low-skill workers, while it increases for high-skill workers. Public benefit use rises among low-skill workers, reflecting both lower earnings and higher reliance on in-kind public services, and declines for high-skill workers. In the other destinations, the opposite pattern emerges as improving labor-market conditions for low-skill workers reduce their reliance on public benefits.

Fiscal outcomes (Figure 2.3, bottom-right panel) are shaped primarily by wage adjustments rather than migrant composition alone. In Germany, fiscal contributions from high-skill workers improve as higher wages raise tax revenues, while the fiscal impact of low-skill workers deteriorates sharply due to lower wages and increased reliance on public benefits. In the remaining destinations, fiscal improvements are driven mainly by the low-skill group: as low-skill workers exit toward Germany, their wages and tax contributions rise in the sending countries.

Hence, policies aimed at attracting low-skill migrants address labor market shortages but generate severe fiscal costs from the targeted group. Competing destinations benefit not only from attracting displaced skilled workers but also from improved conditions for their remaining low-skill workforce. Italy's production decline despite receiving skilled workers shows that production technology parameters mediate spillover effects.

Figure 2.3: Scenario 1



Notes: This figure reports percentage changes relative to the baseline equilibrium following a reduction in migration costs for low-skill workers in Germany, holding policies in other countries constant. Panels show changes in skill composition, wages, aggregate production, private benefit consumption, public benefit consumption, and fiscal impact by skill group across Germany (DE), Spain (ES), France (FR), Italy (IT), and the United Kingdom (UK). Skill shares refer to the proportion of high-skill (HS) and low-skill (LS) households. Wage changes reflect general-equilibrium adjustments to labor supply. Private benefits capture cash-based transfers and market consumption, while public benefits correspond to in-kind services such as education and health care. Fiscal impact is defined as taxes paid minus public and private benefits received. All effects incorporate endogenous migration responses, wage adjustments, and cross-country spillovers.

Southern Europe Opens to Low-Skill Immigrants

Figure 2.4 reports the effects of a coordinated policy reform in which Italy and Spain reduce immigration barriers for low-skill workers to address demographic pressures and labor shortages in low-skill intensive sectors. By lowering mobility costs selectively for low-skill households, the reform induces a reallocation of migrant flows toward Southern Europe and away from Northern destinations.

As shown in Figure 2.4 (top-left panel), both Italy and Spain experience increases in the low-skill share of migrants, accompanied by corresponding declines in the high-skill share. Germany, France, and the United Kingdom exhibit the opposite adjustment, reflecting endogenous migrant self-selection away from Southern Europe among high-skill households.

These compositional shifts generate heterogeneous wage responses (Figure 2.4, top-right panel). In Italy and Spain, the inflow of low-skill workers depresses low-skill wages, while high-skill wages also decline through general equilibrium effects. In contrast, Northern European countries experience rising high-skill wages and declining low-skill wages as a result of complementary labor reallocation.

Production effects diverge sharply between the two implementing countries (Figure 2.4, middle-left panel). Spain experiences a substantial output contraction, reflecting its strong reliance on high-skill labor in production. Italy instead registers a production increase despite adopting the same policy. This difference arises from Italy's production structure, placing relatively greater weight on low-skill labor, allowing it to absorb low-skill immigration more efficiently. Germany, France, and the United Kingdom benefit from redirected high-skill workers and record moderate production gains.

Private and public benefit adjustments mirror labor-market outcomes (Figure 2.4, middle-right and bottom-left panels).

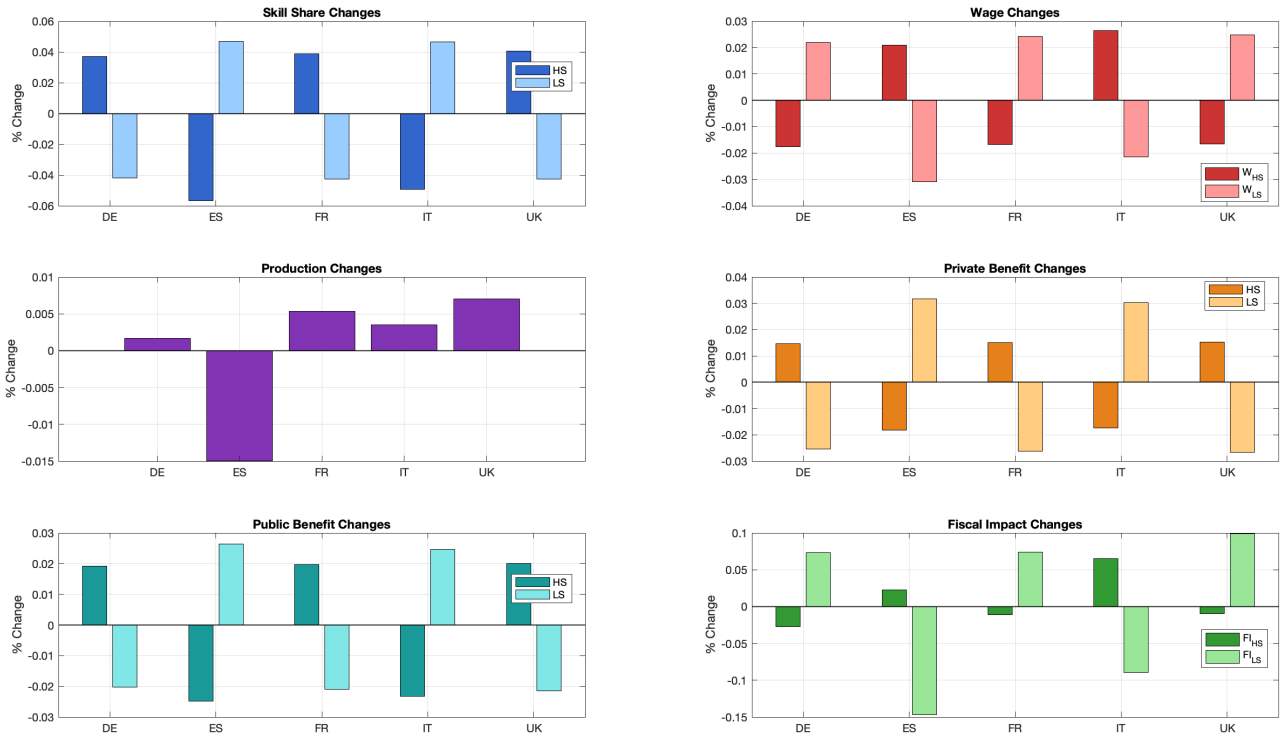
Fiscal impacts (Figure 2.4, bottom-right panel) reflect these equilibrium adjustments. In both Italy and Spain, the fiscal contribution of low-skill households deteriorates, driven by wage compression and higher public benefit use. The deterioration is substantially larger in Spain, while Italy limits fiscal losses thanks to its production structure. In Northern European countries, reduced low-skill labor supply raises low-skill wages and improves their fiscal contributions, while high-skill fiscal effects are slightly negative.

Overall, Figure 2.4 highlights that even coordinated low-skill immigration policies can generate markedly different outcomes across destinations. Differences in production technology and wage responses critically mediate how migrant self-selection translates into fiscal consequences, reinforcing the paper's central mechanism that immigration policy affects public finances primarily through endogenous selection and general equilibrium adjustments.

Joint low-skill immigration policies in Southern Europe produce heterogeneous effects even between coordinating countries. Italy's production structure, favoring low-skill labor, allows it to increase production and limit fiscal deterioration, while Spain's high-skill dependent production technology leads to substantial production losses and greater fiscal costs. The difference in fiscal deterioration between Spain and Italy for the same policy intervention shows that production technology parameters critically determine policy outcomes.

Figure 2.4: Scenario 2

Scenario 2: Southern Europe Opens to LS



Notes: This figure reports percentage changes relative to the baseline equilibrium following a coordinated reduction in migration costs for low-skill workers in Italy and Spain. Definitions of variables and fiscal components are as in Figure 2.3.

France Attracts Both Skill Groups

Figure 2.5 presents the effects of a comprehensive immigration reform in which France reduces migration barriers for both high and low-skill households, aiming to alleviate labor shortages across sectors.

As shown in Figure 2.5 (top-left panel), despite designing a balanced policy, France attracts more low-skill workers than high-skill workers: the high-skill share decreases while the low-skill share increases substantially. This asymmetric outcome reflects France's baseline migration cost structure and its relative position in the European labor market: for high-skill workers, France competes with Germany and the UK which offer higher wages, while for low-skill workers, France offers relatively better conditions compared to alternatives. Other countries experience modest skill share changes receiving some of the high-skill workers who choose not to migrate to France.

Wage responses reflect these compositional changes (Figure 2.5, top-right panel). Wage effects in other countries go in the opposite direction.

Production effects (Figure 2.5, middle-left panel) show France experiencing an output contraction: this reflects the loss of high-skill labor, to which French production is particularly sensitive, combined with an inflow of low-skill workers who contribute less to output per capita. Spain instead benefits from redirected high-skill labor and records the largest production increase among countries.

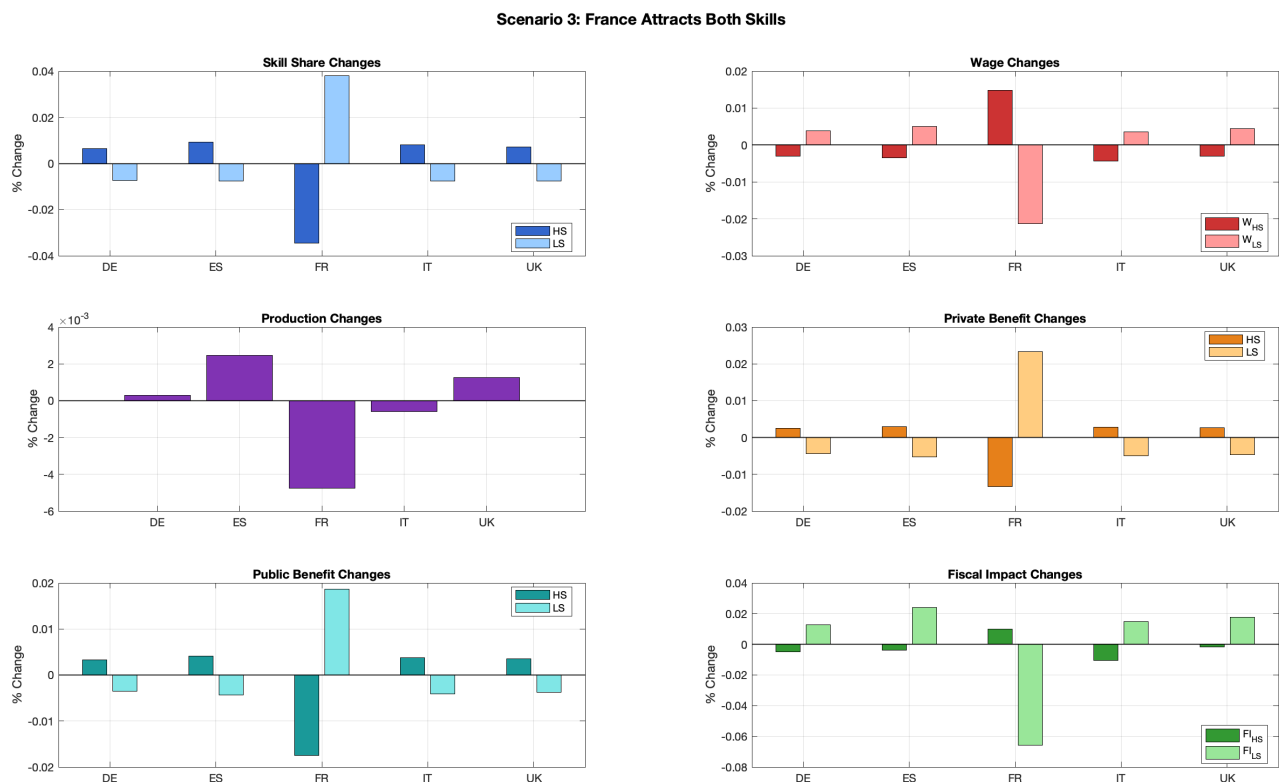
Private and public benefit adjustments mirror these labor-market dynamics (Figure 2.5, middle-right and bottom-left panels). In France, private benefit consumption increases for low-skill households and declines for high-skill ones, and public benefit use rises among low-skill workers and falls among high-skill ones. These shifts reflect both

wage changes and the altered composition of the workforce. Other countries display small benefit responses consistent with their smaller migration inflows.

Fiscal consequences are shown in Figure 2.5 (bottom-right panel). France's fiscal impact from high-skill workers deteriorates due to reduced wages and smaller numbers, while fiscal impact from low-skill workers shows modest improvement reflecting their wage gains.

Comprehensive immigration policies targeting both skill levels may produce unintended compositional effects. France's attempt to attract both worker types disproportionately attracted low-skill workers, leading to production declines and unfavorable fiscal outcomes from skilled workers. This scenario highlights the importance of accounting for relative destination attractiveness and endogenous self-selection in shaping actual versus intended outcomes.

Figure 2.5: Scenario 3



Notes: This figure reports percentage changes relative to the baseline equilibrium following a reduction in migration costs for both high-skill and low-skill workers in France. Variable definitions and fiscal components are as in Figure 2.3.

Italy Attracts High-Skill Immigrants

Figure 2.6 reports the effects of a targeted immigration reform in which Italy lowers migration barriers exclusively for high-skill workers, while maintaining existing restrictions for low-skill migration.

As shown in Figure 2.6 (top-left panel), the reform succeeds in altering the skill composition of the Italian workforce: the high-skill share increases by roughly 2 percentage points, while the low-skill share declines. This adjustment is mirrored in the rest of Europe, where Germany, Spain, France, and the United Kingdom experience modest reductions in high-skill shares and corresponding increases in low-skill shares as workers reallocate toward Italy.

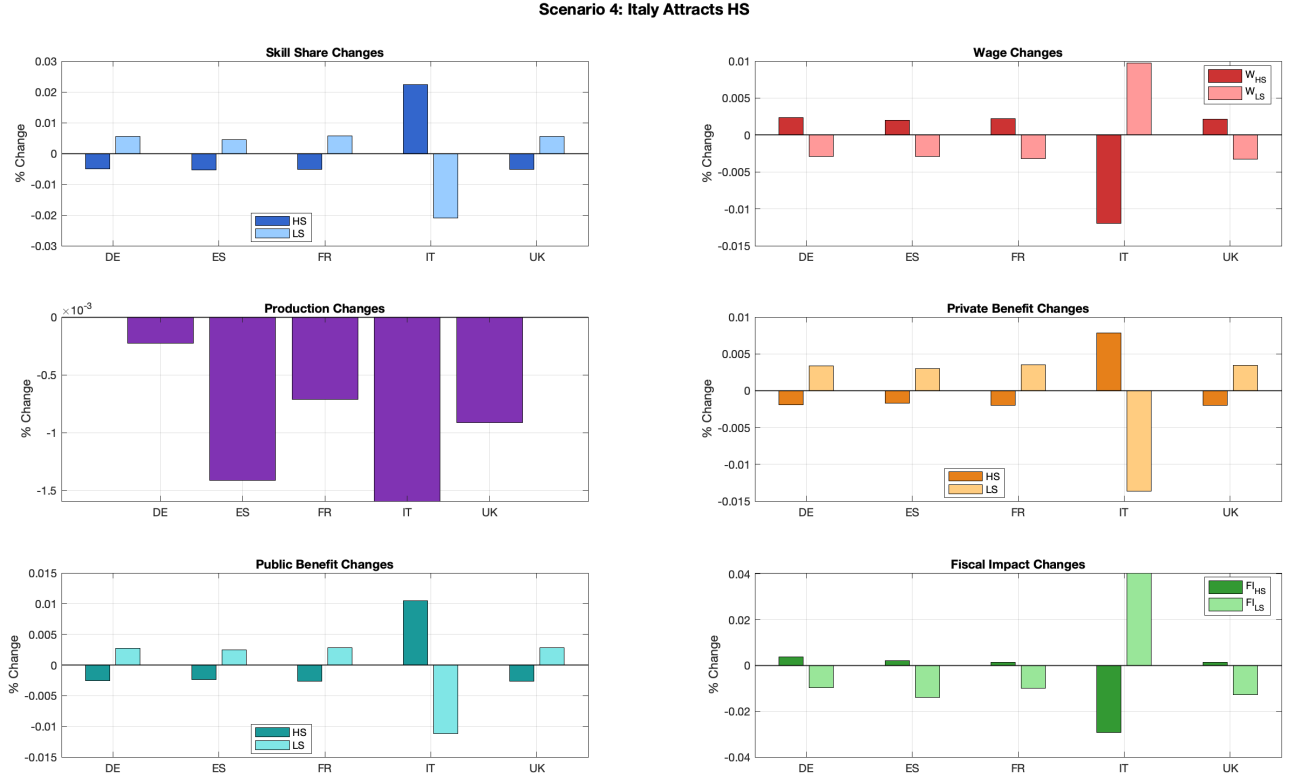
Labor-market effects follow directly from these compositional changes (Figure 2.6, top-right panel). In Italy, high-skill wages decline as increased supply exerts downward pressure, while low-skill wages rise slightly due to relative scarcity. In the other countries, the opposite pattern emerges.

Despite the successful attraction of skilled labor, aggregate production declines in all countries, including Italy itself (Figure 2.6, middle-left panel). Italy experiences a noticeable output contraction, while Spain, France, and the United Kingdom also register negative production responses while Germany shows the smallest decline. This shared production loss occurs for two related reasons. First, Italy's production structure actually favors low-skill labor ($\gamma_0 > \gamma_1$), so attracting high-skill workers does not efficiently leverage Italy's comparative advantage. Second, Italy draws skilled workers from other European destinations rather than from outside the modeled region given the framework, creating a zero-sum reallocation that disrupts production across all countries without adding to the total European workforce. The adjustment costs of this reallocation exceed any efficiency gains from matching workers to destinations.

Fiscal consequences are summarized in Figure 2.6 (bottom-right panel). Following the wage driven mechanism, Italy's fiscal impact from high-skill workers worsens: the wage compression from increased supply reduces their tax contributions despite the larger number of skilled workers. Conversely, Italy's fiscal impact from low-skill workers improves as their rising wages (due to substitution effects) increase their tax payments relative to baseline. Other European countries experience the mirror pattern: their fiscal impact from high-skill workers improves as reduced supply raises wages and tax contributions, while their fiscal impact from low-skill workers deteriorates as incoming low-skill workers (who find these destinations relatively more attractive given Italy's high-skill focus) depress wages and reduce tax contributions in that segment.

Targeted high-skill immigration programs within Europe operate as zero-sum or negative-sum games when attracting workers from other EU destinations rather than from outside the region. The overall production level declines affecting every country including the implementing one, showing that intra-European competition for skilled workers may reduce aggregate production.

Figure 2.6: Scenario 4



Notes: This figure reports percentage changes relative to the baseline equilibrium following a reduction in migration costs for high-skill workers in Italy. Variable definitions and fiscal components follow those in Figure 2.3.

Coordinated Low-Skill Immigration in Northern Europe

Figure 2.7 illustrates the effects of a coordinated immigration reform in which Germany, France, and the United Kingdom simultaneously reduce migration barriers for low-skill workers.

The policy generates compositional effects (Figure 2.7, top-left panel): all three implementing countries experience substantial increases in low-skill labor shares and corresponding declines in high-skill shares, as Northern Europe becomes collectively more attractive to low-skill migrants. In contrast, Italy and Spain experience the opposite adjustment: their high-skill shares rise, by roughly 4 percentage points, while low-skill shares decline. This pattern reflects strong self-selection responses once substitution across Northern destinations is removed.

Labor-market effects follow directly from these reallocations (Figure 2.7, top-right panel).

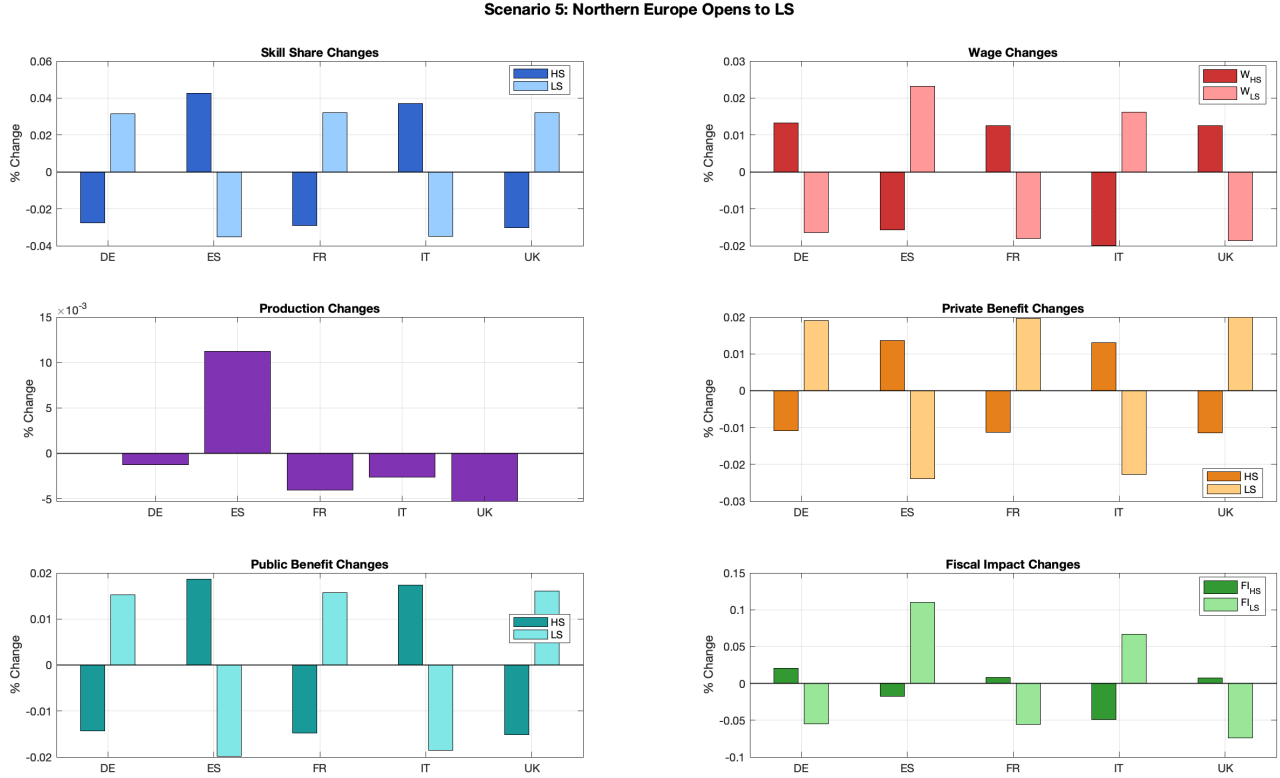
Production responses (Figure 2.7, middle-left panel) shows Spain recording the largest production increase driven by an inflow of high-skill workers to which Spanish production is particularly sensitive. In contrast, Germany, France, and the United Kingdom all suffer production declines as their labor forces shift toward less skill-intensive compositions.

Fiscal consequences are summarized in Figure 2.7 (bottom-right panel). Following the wage-driven mechanism, the fiscal patterns reflect labor supply changes in each country. In Northern Europe (Germany, France, United Kingdom), the influx of low-skill workers depresses their wages and worsens fiscal impact, while the relative scarcity of high-skill workers raises their wages and improves fiscal impact. In Southern Europe, Spain and Italy experience the mirror pattern. Spain's large improvement in low-skill fiscal impact

represents the most positive change for any single skill-country combination in this scenario. Italy shows a similar pattern but with more modest magnitudes.

Coordinated low-skill immigration policies across Northern Europe benefit Southern European destinations at Northern Europe's expense. Spain's production and fiscal gains demonstrate that coordinated low-skill immigration policies within a subset of countries can generate strong spillovers to non-participating regions.

Figure 2.7: Scenario 5



Notes: This figure reports percentage changes relative to the baseline equilibrium following a coordinated reduction in migration costs for low-skill workers in Germany, France, and the United Kingdom. Variable definitions and fiscal components follow those in Figure 3.

Cross-Country Comparison

Figure 2.8 summarizes the percentage change in total fiscal impact across countries and counterfactual policy scenarios. Taken together, the scenarios reveal systematic cross-country patterns that clarify the general equilibrium mechanisms through which immigration policy affects self-selection and fiscal outcomes in an integrated European labor market.

The dominant channel through which migration policies affect fiscal outcomes operates through wages. When a country successfully attracts migrants of a particular skill type, the resulting increase in labor supply compresses wages for that group, reducing tax revenues and worsening the fiscal contribution of the very workers the policy aims to attract. At the same time, countries that lose workers experience the mirror effect: reduced labor supply raises wages for the remaining workforce, improving their fiscal contribution. As a result, migration policies generate cross-border fiscal externalities that propagate through wage adjustments rather than through mechanical changes in population composition.

The magnitude and direction of these wage-driven fiscal effects depend critically on countries' production structures. Spain emerges as the most fiscally sensitive country

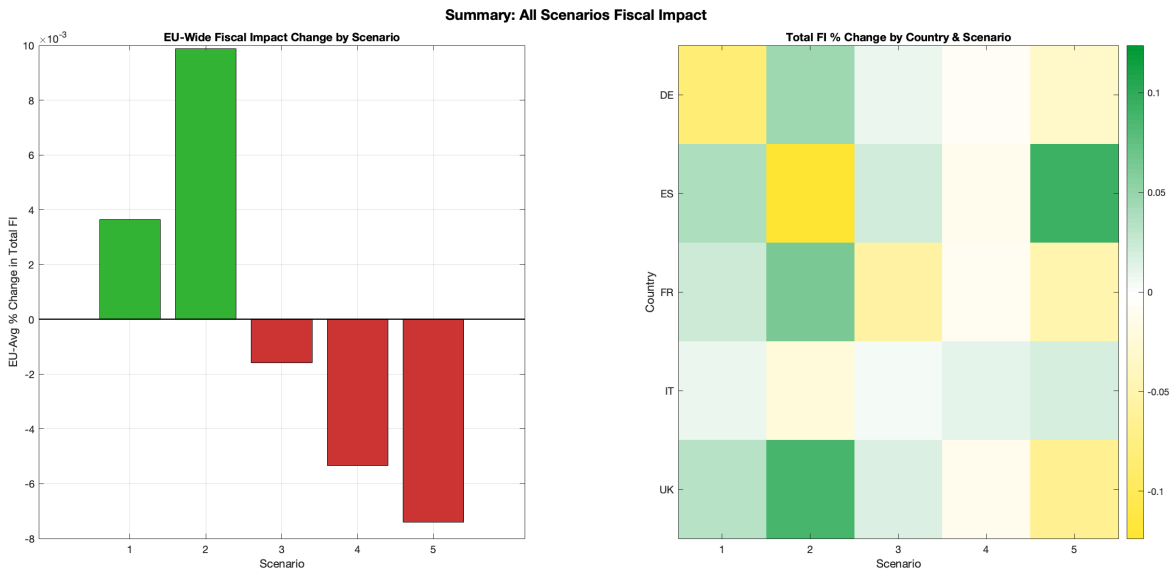
in the sample, reflecting the large disparity between its high-skill and low-skill production weights. This asymmetry implies that shifts in skill composition translate into particularly large changes in marginal productivity, wages, and fiscal outcomes. Italy, by contrast, consistently displays response patterns that diverge qualitatively from those of other countries, often moving in the opposite direction. This behavior is rooted in Italy’s distinctive production structure, where the weight on low-skill labor exceeds that on high-skill labor—a reversal of the ordering observed in Germany, France, Spain, and the United Kingdom. Under the CES production function, this implies that identical migration shocks generate fundamentally different labor market and fiscal responses across countries.

Substitutability between skill types further amplifies these effects. Because high-skill and low-skill workers are substitutes in production, an inflow of one skill group not only depresses wages for that group but also raises the marginal productivity and wages of the other group. This interaction reinforces the wage channel and helps explain why fiscal outcomes often improve for the skill group that becomes scarcer, even when policy targets the opposite group.

Coordinated policy scenarios reveal an additional layer of complexity. When multiple countries simultaneously adjust migration incentives, worker reallocation occurs not only between participating and non-participating countries, but also within the coordinating group itself. As a result, coordination reshapes competitive pressures without eliminating spillovers, producing heterogeneous outcomes even among countries implementing similar policies.

Taken together, these mechanisms carry important implications for policy design. Unilateral migration policies inevitably generate fiscal spillovers that individual governments cannot internalize. The direction and magnitude of these spillovers depend on cross-country heterogeneity in production structures, while the wage channel ensures that policies aimed at attracting fiscally beneficial migrants may paradoxically worsen fiscal outcomes by compressing the wages that generate tax revenues in the first place.

Figure 2.8: Cross-country Comparison



Notes: The left panel reports the average percentage change in total fiscal impact across the five destination countries for each policy scenario. The right panel displays country-specific percentage changes in total fiscal impact, highlighting the heterogeneity of fiscal responses across destinations. Positive values indicate fiscal improvements relative to the baseline equilibrium, while negative values denote fiscal deteriorations.

2.5 Conclusion

This paper develops a unified framework to analyze the fiscal impact of immigration in Europe, integrating immigration policy and migrant self-selection within a general equilibrium model. Using household-level data from EU-SILC and a structural approach that combines a multinomial logit migration model with a CES production technology, the analysis quantifies how policy-induced changes in migration costs shape the skill composition of migrant inflows and, through labor-market adjustments, determine fiscal outcomes across destination countries.

The main findings can be summarized along three dimensions. First, the wage channel emerges as the dominant mechanism through which immigration policy affects public finances. When a country reduces barriers to entry for a particular skill group, the resulting increase in labor supply compresses wages for those workers, reducing their tax contributions and worsening their fiscal impact. This result implies that policies aimed at attracting fiscally beneficial migrants may undermine their intended objectives by altering the labor-market conditions that generate tax revenues.

Second, cross-country heterogeneity in production structure mediates the fiscal consequences of migration policy. Italy’s distinctive production technology, in which low-skill labor carries greater weight than high-skill labor, generates response patterns that diverge qualitatively from those observed in Germany, France, Spain, and the United Kingdom. Spain, by contrast, exhibits the highest sensitivity to skill-composition shocks due to the large disparity between its high-skill and low-skill production weights. These differences imply that identical policy interventions produce different outcomes across destinations, highlighting the importance of accounting for local economic structures when designing migration policy.

Third, unilateral migration policies generate fiscal externalities that propagate across borders through migrant reallocation. Countries that lose workers to more attractive destinations benefit from reduced labor supply, rising wages, and improved fiscal contributions from their remaining workforce. Coordinated policy scenarios show that when multiple countries implement similar reforms, the redistribution of migrants occurs both between participating and non-participating countries and within the coordinating group itself. These spillovers suggest potential gains from policy coordination that unilateral national approaches cannot capture.

Taken together, these results highlight that the fiscal effects of immigration policy operate primarily through migrant self-selection and subsequent labor-market adjustment. Changes in entry barriers alter the skill composition of migrant inflows, which in turn affect wages and tax bases through general-equilibrium mechanisms. As a result, fiscal outcomes cannot be inferred directly from the intended skill targeting of a policy, but emerge endogenously from the interaction between self-selection and country-specific production structures. Moreover, in an integrated European labor market, national immigration reforms generate cross-border spillovers through the reallocation of migrants across destinations, implying that unilateral policies partly redistribute fiscal effects rather than determine them in isolation. From a policy perspective, these findings underscore the importance of evaluating migration reforms within a framework that explicitly links immigration policy to migrant self-selection and fiscal outcomes and that accounts for cross-country heterogeneity and spillovers when assessing policy impacts.

Chapter 3

Household Dynamics and Labor Reallocation within Migrant Sending Households

Joint with Gargi Dangwal and Maria Jimena Romero

3.1 Introduction

In many low-income countries, internal migration separates households for extended periods. In India, nearly 80 percent of labor migrants are men, but only a quarter move with their families.¹ As a result, millions of households are left to navigate temporary separation, adjusting economic and social behavior in the absence of a working-age adult. Family members reallocate labor within and outside home, balance education decisions against new time demands, and shift household priorities in response to both the loss of local earnings and the inflow of remittances. These adjustments may be transitory, confined to the period of separation, or may leave lasting effects on labor supply and human capital accumulation.

This paper studies how households respond to temporary internal migration using high-frequency panel data from the Consumer Pyramids Household Survey (CPHS) in India. We focus on episodes of male migration that induce separation and examine how household behavior evolves before departure, during absence, and after return. To guide the empirical analysis, we develop a simple collective household framework that characterizes household decisions at the onset of migration, when separation occurs and resource constraints and intra-household decision-making weights shift. The model provides theoretical predictions regarding labor reallocation, schooling choices, and asset adjustments during separation, which we evaluate in the data.

Our empirical strategy combines two complementary approaches designed to map these predictions into the data while addressing identification concerns. First, we exploit the panel's granularity to implement a staggered difference-in-differences (DCDH) framework that estimates household responses as migration unfolds. Second, to address endogeneity concerns and strengthen causal identification, we employ a shift-share instrument variable (SSIV) that captures labor demand shocks driven by exogenous international commodity price variation, specifically in manufacturing sectors that are key destinations for internal migrants. The instrument combines price driven shocks at potential destinations with variation in exposure across households, allowing us to isolate plausibly exogenous changes in migration opportunities at the district level. While these shocks may also induce broader general equilibrium effects, we interpret our estimates as capturing the

¹Nayyar and Kim (2018b); Vikram (2021)

consequences of a commodity driven labor demand boom. In this sense, our findings are best understood as a case study of household responses to migration opportunities triggered by external economic forces. This allows us to isolate plausibly exogenous variation in migration opportunities at the district level, while preserving the high frequency of our panel.

Both the difference-in-differences and the shift-share instrumental variable approaches yield qualitatively similar results, suggesting that the observed transformations in labor supply, income composition, and asset accumulation reflect robust behavioral responses to migration. The convergence of these two empirical narratives strengthens our confidence in the interpretation of these effects.

Our analysis draws on the Consumer Pyramids Household Survey (CPHS), a high-frequency panel conducted by the Centre for Monitoring Indian Economy (CMIE), which enables us to track household responses to migration over time. The CPHS follows approximately 232,000 households across India from 2014 to 2019, surveying each household every four months. It is nationally representative and provides detailed information on migration decisions, household income, education, employment, borrowings, investments, and other socio-economic indicators, allowing us to observe behavioral adjustments.

To construct our shift-share measure of exposure to migration opportunities, we supplement the CPHS with two additional data sources. First, we use international commodity price indices from the International Monetary Fund as plausibly exogenous shocks to output prices in export oriented manufacturing sectors. Second, we use district level industrial composition data from the 2010 wave of the Annual Survey of Industries, administered by the Ministry of Statistics and Programme Implementation, to proxy each region's baseline exposure to these sectoral shocks. These data allow us to construct a shift-share design that captures spatial and temporal variation in migration opportunities induced by global demand fluctuations.

We begin by examining how household income composition responds to migration-induced separation. Across both identification strategies, migration reduces income generated at origin, driven by the loss of wage and production income. Remittances increase but do not fully offset this decline, leaving average per-capita income broadly unchanged. Beneath this aggregate stability, however, there is substantial heterogeneity: poorer households tend to experience net gains in per-capita resources, while wealthier households face net losses, reflecting differences in reliance on local wages versus remittance inflows. These patterns reverse upon reunification, as wage income is restored and remittances decline, again leaving per-capita income largely unchanged².

Households adjust to these income shifts through substantial reallocation of labor. Spouses respond to separation by increasing labor market participation and reducing unpaid work, with these adjustments concentrated among poorer households. The nature of this reallocation differs by context, with rural households shifting toward farming and informal work and urban households toward self-employment and small business activity. Other working-age members also increase labor supply during separation, primarily at the expense of schooling, indicating a substitution away from human capital accumulation. These labor responses largely reverse after the migrant's return, particularly for spouses.

Asset responses are more persistent. Migration is accompanied by broad declines in household asset holdings, consistent with partial decapitalization during separation. While many consumer durables recover after reunification, productive agricultural assets show little rebound, suggesting that temporary migration shocks can induce lasting changes in household investment portfolios.

²Our income measure does not include wages earned by the migrant at the destination, and thus captures only the income retained at the origin household.

Literature and Contribution - A large literature has examined the consequences of migration for those left behind, especially with regard to labor supply, education, and asset accumulation. One central margin of adjustment is labor reallocation within the household. When men migrate, their absence often increases the domestic and market work burden on remaining members, particularly women and children, especially in settings where formal employment is scarce or cultural constraints limit female work outside the home³. At the same time, several studies document that this disruption can expand autonomy, mobility, and decision-making power for women, leading to greater access to productive resources⁴.

Among children, outcomes vary widely. Some studies report that migration leads to increases in school enrollment, particularly for girls, either because of remittances that relax credit constraints or because of temporary changes in household decision-making⁵. However, others find that daughters disproportionately absorb the labor loss, which can reduce their school participation⁶. A broader set of studies highlight negative effects on education and well-being due to reduced parental inputs⁷, higher opportunity costs to schooling⁸, and emotional burdens placed on children⁹. At the same time, a complementary body of work emphasizes the potential for migration to improve household welfare through remittance flows¹⁰ or to generate “beneficial brain drain” effects by raising the perceived returns to schooling¹¹.

One mechanism that links these divergent outcomes is intra-household bargaining. If migration shifts bargaining power, temporarily or permanently, it may lead to systematic changes in how resources and responsibilities are allocated. [Antman \(2015\)](#), for example, finds that in Mexico, households spend more on girls when the male head migrates, with this pattern reversing upon his return. [Binzel and Assaad \(2011\)](#) suggests that if bargaining is shaped by income shares, then the exit of a migrant could actually weaken the bargaining position of non-migrant members, especially where outside labor options are limited.

Despite these insights, key gaps remain. First, much of the literature provides a static view, either a one time measurement or a cross-sectional correlation, leaving open questions about how households adjust dynamically across the different phases of migration. Second, the focus has largely been on international or permanent migration, whereas temporary internal migration remains the dominant form of mobility across developing countries and arguably the one with the most direct impact on vulnerable households. Third, most existing studies emphasize effects on the nuclear unit, i.e. spouses and children, without systematically examining the behavior of other household members. In settings like India, where extended families and joint households are common, this is a critical omission. Understanding how young adults or older dependents substitute for the absent migrant, sometimes by cutting short their education or taking up low quality work, is essential for capturing the full cost of migration induced disruption to household structure and intergenerational mobility.

We contribute to filling these gaps in several ways. First, we provide one of the first

³Torres and Carte (2016); Wu and Ye (2014); Binzel and Assaad (2011); Mahapatro (2018)

⁴Iqbal et al. (2014); Agadjanian and Hayford (2018)

⁵Acosta (2011a); Antman (2011b); Clemens and Tiongson (2017); Mobarak et al. (2021)

⁶de Brauw et al. (2018); Wu and Ye (2014); Gao et al. (2023a); Binzel and Assaad (2011)

⁷Giannelli and Mangiavacchi (2010b); Lahaie et al. (2009); Zhang et al. (2014)

⁸de Brauw and Giles (2017); McKenzie and Rapoport (2011a)

⁹Jampaklay (2006); Giannelli and Mangiavacchi (2010a)

¹⁰Edwards and Ureta (2003); López-Córdova (2005); Yang (2008a)

¹¹Batista et al. (2007); Docquier and Rapoport (2012); Beine et al. (2008a)

dynamic estimates of household responses to temporary internal male migration in a large developing country setting. Using high frequency panel data from India, we track changes in labor supply, income composition, education, and asset ownership before, during, and after migration episodes, rather than relying on a single point in time. This allows us to distinguish between short run coping mechanisms and more persistent structural shifts. Second, we implement two complementary identification strategies: a staggered difference-in-differences framework that traces within household adjustments over time, and a shift-share instrumental variables approach based on exogenous commodity price shocks in destination manufacturing sectors. The convergence in results across these strategies enhances the robustness of our findings.

Third, we document how migration restructures household labor. In addition to spousal responses, which include substantial increases in farming and informal work for poorer rural households and urban self employment for others, we also uncover sharp changes among other members of the household. Young adults, especially men, appear to substitute away from human capital accumulation, exiting education and increasing work participation. This finding is especially relevant in contexts where the long run costs of such trade offs may be hidden but substantial. By going beyond the nuclear unit, we offer a richer picture of the intra household dynamics triggered by temporary migration.

Finally, we show that these shifts in labor and asset portfolios do not always reverse after the migrant returns. Households experience declines in productive asset ownership, especially tractors and cattle during separation, with little sign of recovery post return. In contrast, consumer durables and mobility goods do rebound, consistent with resumed remittance flows or restored financial control. Our results thus complement and extend recent work such as [Madhok et al. \(2022\)](#) that documents persistent shifts in women’s economic activity following migration episodes. We add to this literature by showing that other forms of adjustment, including in asset portfolios and the educational trajectories of non-spousal members, also endure, pointing to broader household reorganization even in the face of temporary shocks.

Together, these findings offer a more comprehensive and temporally nuanced understanding of how temporary internal migration reshapes household behavior in settings marked by informal labor markets, extended family structures, and ongoing cycles of male migration.

The paper proceeds as follows. Section 2 outlines the theoretical framework. Section 3 describes the data. Section 4 presents the empirical strategy, combining a difference-in-differences event study with a shift-share instrument for causal identification. Section 5 reports the results. Section 6 concludes.

3.2 Conceptual Framework

This section presents a static collective household model that motivates the empirical analysis of household separation and resource reallocation. The model captures household adjustments at the onset of temporary male migration, when remittances partially, but not fully, offset the loss of labor income at origin. The empirical counterparts of these mechanisms are examined in detail in [Section 3.5.3](#).

3.2.1 Household Composition and Resource Allocation

We consider a household consisting of the following members: a male household head m , a female spouse f and young adults y . Before migration, the male household head works full-time and contributes a fixed income w_m to the household such that $l_m = 1$. We

assume that the male household head contributes no time to unpaid home production, such that $h_m = 0$. The female spouse allocates her time between paid work l_f and unpaid home production h_f (which could be caregiving work at home). The young adults (youth) divide their time between paid labor l_y and schooling s_y . Following migration, the male household head is no longer present in the household and sends home remittances R . We assume that male household head migration results in a net income loss for the household¹². While remittances R are received from the absent male household head, they are not enough to fully replace the wage w_m he would have earned at home, hence:

$$R < w_m l_m \quad (3.1)$$

Each member has a unit time constraint:

$$l_m = 1, \quad l_f + h_f = 1, \quad l_y + s_y = 1. \quad (3.2)$$

The household's total monetary income Y before the migration of the household head consists of his labor earnings, female labor earnings and the young adults' earnings.

$$Y^{pre} = w_f l_f^{pre} + w_y l_y^{pre} + w_m \quad (3.3)$$

The household's total monetary income after the household head migrates consists of female labor earnings, the young adults' earnings, and remittances from the absent male:

$$Y^{post} = w_f l_f^{post} + w_y l_y^{post} + R \quad (3.4)$$

This income is allocated to the consumption of household members and to the purchase of market goods x that complement unpaid labor in producing household services:

$$Y^{pre} = c_f + c_y + c_m + px \quad (3.5)$$

Post-migration, $c_m = 0$

3.2.2 Home Production and Preferences

The household produces some home-produced services H , such as caregiving, food preparation, or cleaning. These services are produced through Leontief technology using unpaid labor from the female spouse and a market input x :

$$H = \min\{h_f, x\} \quad (3.6)$$

This implies that one unit of home production requires one unit of unpaid female labor and one unit of the market input x . Under this assumption, the female sets

$$x = h_f = 1 - l_f. \quad (3.7)$$

Each household member derives utility from private consumption and non-market activities. Preferences are separable and logarithmic in consumption and in schooling or home production (depending on the individual).

Pre-Migration

Before migration the male derives utility only from supplying inelastically a unit $l_m = 1$ of paid work, so it has no choice variable to optimize. The female spouse derives utility from her own consumption, minus a subsistence consumption level, and from the level of home production. Hence, the female maximize the following:

$$\begin{aligned} \max_{l_f} \quad & U_f = \alpha_f \ln(c_f - \epsilon_f) + (1 - \alpha_f) \ln(H) \\ \text{s.t.} \quad & c_f = \theta_f Y, \quad H = \min\{h_f, x\} \end{aligned} \quad (3.8)$$

¹²We show in Section 3.5.3 that the household experiences a net loss at $t = 0$ when the household head migrates.

Here θ_f is the share of income consumed from the female and

$$\theta_f + \theta_m + \theta_y = 1. \quad (3.9)$$

The young adults derive utility from consumption, minus a subsistence consumption level, and schooling. Hence, they maximize the following:

$$\begin{aligned} \max_{l_y} \quad & U_y = \alpha_y \ln(c_y - \epsilon_y) + (1 - \alpha_y) \ln(s_y) \\ \text{s.t.} \quad & c_y = \theta_y Y, \quad s_y = 1 - l_y \end{aligned} \quad (3.10)$$

Solving the problem of the female spouse we get the following first-order condition and best response function:

$$\begin{aligned} \text{F.O.C.} \quad & \alpha_f \cdot \frac{\theta_f w_f}{\theta_f Y - \epsilon_f} = \frac{(1 - \alpha_f)\rho}{1 - l_f} \\ l_f = & \frac{\alpha_f w_f - \rho(1 - \alpha_f)(w_m + w_y l_y - \frac{\epsilon_f}{\theta_f})}{w_f[\alpha_f + (1 - \alpha_f)p]} \end{aligned} \quad (3.11)$$

For the young adults instead, we get the following:

$$\begin{aligned} \text{F.O.C.} \quad & \alpha_y \cdot \frac{\theta_y w_y}{\theta_y Y - \epsilon_y} = \frac{(1 - \alpha_y)}{1 - l_y} \\ l_y = & \frac{\alpha_y w_y - (1 - \alpha_f)(w_m + w_f l_f - \frac{\epsilon_y}{\theta_y})}{w_y} \end{aligned} \quad (3.12)$$

From the best response functions we get the following equilibrium allocations, for the female spouse:

$$l_f^{*pre} = \frac{\alpha_f w_f - (1 - \alpha_f)\rho(\alpha_y(w_m + w_y) + (1 - \alpha_y)\frac{\epsilon_y}{\theta_y} - \frac{\epsilon_f}{\theta_f})}{w_f(\alpha_f + (1 - \alpha_f)\rho\alpha_y)} \quad (3.13)$$

And for the young adults

$$l_y^{*pre} = \frac{\alpha_y w_y - (1 - \alpha_y)(w_m + \frac{\alpha_f w_f - (1 - \alpha_f)\rho(\alpha_y(w_m + w_y) + (1 - \alpha_y)\frac{\epsilon_y}{\theta_y} - \frac{\epsilon_f}{\theta_f})}{\alpha_f + (1 - \alpha_f)\rho\alpha_y} - \frac{\epsilon_y}{\theta_y})}{w_y} \quad (3.14)$$

Post-Migration

Following migration, the male member is absent from the household and no longer participates in local paid labor. Instead, the household receives a fixed remittance income $R < w_m$. As a result, the total household income becomes Equation (3.4) and the resource-sharing rules remain unchanged

$$C_f = \theta_f Y, \quad C_y = \theta_y Y$$

with

$$\theta_f + \theta_y = 1 \quad (3.15)$$

reflecting that the male is no longer included in intra-household consumption allocation. Consequently, the new equilibrium allocation post-migration for the female spouse is:

$$l_f^{*post} = \frac{\alpha_f w_f - (1 - \alpha_f)\rho(\alpha_y(R + w_y) + (1 - \alpha_y)\frac{\epsilon_y}{\theta_y} - \frac{\epsilon_f}{\theta_f})}{w_f(\alpha_f + (1 - \alpha_f)\rho\alpha_y)} \quad (3.16)$$

And for the young adults:

$$l_y^{*post} = \frac{\alpha_y w_y - (1 - \alpha_y) \left(R + \frac{\alpha_f w_f - (1 - \alpha_f) \rho \left(\alpha_y (R + w_y) + (1 - \alpha_y) \frac{\epsilon_y - \epsilon_f}{\theta_y - \theta_f} \right)}{\alpha_f + (1 - \alpha_f) \rho \alpha_y} - \frac{\epsilon_y}{\theta_y} \right)}{w_y} \quad (3.17)$$

Compared to the pre-migration case, the remittance R replaces the male's wage w_m , and his consumption weight is eliminated from the sharing rule. These changes influence both l_f and l_y .

3.2.3 Comparative Statics and Theoretical Predictions

To formally assess the implications of male household head migration on household behavior, we derive the comparative statics for the individual labor supply together with the theoretical predictions. We compare the equilibrium labor supply of the female and the young adult in the pre- and post-migration scenarios illustrating how household behavior adjusts in response to the temporary migration of the male household head¹³.

Proposition 1: *Increase in Female Labor Supply*

The female's market labor supply increases following migration if and only if:

$$l_f^{*post} > l_f^{*pre} \quad \Leftrightarrow \quad \frac{\partial l_f^*}{\partial w_m} < 0 \quad (3.18)$$

That is, a reduction in the male wage income (replaced by a lower remittance R) induces a higher labor supply by the female, provided her optimal labor supply is decreasing in the male wage.

Proposition 2: *Increase in Young Adult Labor Supply*

Similarly, the young adults' market labor supply increases post-migration if and only if:

$$l_y^{*post} > l_y^{*pre} \quad \Leftrightarrow \quad \frac{\partial l_y^*}{\partial w_m} < 0 \quad (3.19)$$

That is, the young adult compensates for the loss in household income due to migration by increasing their time in paid labor, conditional on a negative marginal effect of male wages on their optimal labor supply.

Proposition 3: *Decline in Young Adults Schooling*

The time devoted to schooling by the young adults decreases following migration if and only if:

$$s_y^{post} < s_y^{pre} \quad \Leftrightarrow \quad l_y^{post} > l_y^{pre} \quad (3.20)$$

Since schooling time is defined as the residual from total time endowment, i.e., $s_y = 1 - l_y$, any increase in young adult labor supply mechanically implies a decline in time allocated to education. This highlights the indirect cost of migration in terms of foregone human capital investment.

The model's predictions provide a foundation for our empirical strategy. In particular, we examine whether the onset of temporary male migration translates into measurable shifts in household behavior at the point of separation. Specifically, we test whether: (i) the female spouse increases her participation in paid labor, reducing the time allocated

¹³Proofs are provided in Appendix 3.A.1

to home production; and (ii)-(iii) young adults increase their labor supply at the expense of education. These outcomes allow us to assess whether the theoretical trade-offs highlighted by the model between income generation, home production, and human capital investment are borne out in the data.

3.3 Data and Stylized Facts

Our main analysis employs the Consumer Pyramids Household Survey (CPHS) conducted by a private agency called the Centre for Monitoring the Indian Economy (CMIE). This survey is a high-frequency, nationally representative household panel data collected every four months since 2014. Therefore, the execution of the CPHS occurs in three waves throughout a calendar year: the first spanning January through April, the second from May through August, and the third from September through December. CPHS tracks the same household and its members over long periods and contains a broad range of household variables, including detailed consumption and income information, individual employment, education, and demographic characteristics. CMIE has surveyed over 232,000 households between 2014 and 2019, with an annual attrition rate of 3.7%¹⁴. We restrict our main analysis to the 2014–2019 period to avoid the COVID-19 years, during which migration patterns were substantially disrupted.

The advantages of using CMIE-CPHS data include its extensive documentation of individual level migration, making it one of the rare Indian surveys with such detailed tracking. The survey’s ability to follow households across years allows us to incorporate household and individual fixed effects in our analysis, effectively controlling for time invariant unobserved heterogeneity across households. However, the absence of exact migration destinations before 2019 prevents us from fully leveraging labor demand shocks at specific origin-destination pairs and precludes the use of gravity style models that rely on detailed bilateral migration flows. To address this limitation, we define a flexible instrument that considers all potential destination districts, with a reduced influence as the distance increases. Another limitation is the lack of detailed information about the migrants themselves. Nonetheless, this does not significantly impact our analysis, as we focus on the changes in household composition and income in the migrant sending households, as well as the labor supply decisions of the remaining household members, for whom we have comprehensive data.

To construct our shift-share instrumental variable, we draw data from multiple sources. Monthly commodity price indices are obtained from the International Monetary Fund. District-level export values by industry are sourced from the 2010 wave of the Annual Survey of Industries, administered by the Ministry of Statistics and Programme Implementation.

3.3.1 Treatment Definition

Our analysis focuses on household separation resulting from the migration of the male household head, which we define as the treatment. Treatment status is identified in three steps.

First, we clarify what constitutes a household at the origin. In CMIE, a household is a physical structure where individuals reside. The survey records current occupants, i.e., members who have lived in the household for at least the past four months and

¹⁴Defined as the average percentage of households that were not present in any survey in the previous year.

share meals from a common kitchen. Household composition can change through births, deaths, immigration (e.g., returning migrant workers or students), and emigration (when members leave for marriage, work, or study). The CPHS tracks the status of emigrated members but does not update their socioeconomic information while they are away. As a result, the survey provides rich data on individuals while present in the household, but not once they have left.

Second, migration status is recorded in the household roster. An individual is coded as a migrant if their status is listed as "emigrated", meaning they reside elsewhere at the time of the survey.

Finally, we define treatment as household separation caused by the migration of the male household head without his spouse. Male household heads are identified as working-age (18–65) men who either (i) designate themselves as the “household head” or (ii) are married prior to their first recorded migration episode. A separation event occurs when such a male household head migrates without a working-age spouse or another married working-age female.¹⁵ This event defines our treatment, and we study its effects on the labor supply, income, asset accumulation, and human capital outcomes of the members who remain behind.

3.3.2 Sample Selection

The CPHS panel tracks 232,636 households between 2014 and 2019. Among these, 90,264 households reported at least one migration episode, and 24,823 involved the migration of a male household head. From this group, 6,435 households experienced a separation event, defined as the migration of the male household head without their spouse. To construct a clean treatment sample, we exclude households where (i) a married female member also migrates during the panel, (ii) the household is already separated at baseline (2014), or (iii) the household is not observed in all waves between 2014 and 2019. After applying these restrictions, our final sample includes 4,703 treated households.

3.3.3 Stylized Facts on Household Migration and Separation

Several stylized patterns stand out from the CMIE panel data. First, individual migration is widespread, while complete family shifts remain rare. By 2019, migration accounted for 20.4% of all individual person-wave observations in the panel (weighted to match the national population). In contrast, family migration, defined as shifts involving multiple household members, was uncommon, occurring in less than 1% of cases.

Second, migration shows a clear upward trend over time. The share of household members reporting migration rose from around 10% in 2016¹⁶ to 20.4% in 2019. Among working-age individuals, female migration slightly exceeded male migration: by 2019, 22.0% of women in this age group had migrated at least once, compared to 19.7% of men.

Third, proximity to major urban centers shapes migration patterns. As shown in Figure 3.A1, the number of working-age male migrants declines with greater average distance to the fifty largest Indian cities.

Fourth, household separation tends to be temporary. Of the 4,703 treated households, 2,042 reported the return of the male household head during 2014–2019. Table 3.A1 shows

¹⁵Marital status is observed directly from 2019 onward. For earlier waves, we impute it based on age and relationship to the household head, cross-validated with post-2019 data.

¹⁶Beginning in 2016 (Wave 8), CMIE revised its panel maintenance protocols to retain households that experienced a complete family shift. Prior to this change, such households were dropped from the sample, potentially under reporting migration.

that the average duration of separation was five quadrimesters (around one year and four months), though this figure reflects censoring at the end of the panel (Figure 3.A2). Among households that experience separation early in the panel (2015–2016), over 60% reunify before the end of the survey period, as shown in Figure 3.A3. For these early-separating households, the average duration of separation exceeds seven quadrimesters, gradually declining for later cohorts as the panel window shortens mechanically. All households begin the panel with the male and female heads residing together, as required by our sample construction. Short-term separations, defined as reunification within one year, are common: 1,320 of the 4,703 households experience a separation lasting three quadrimesters or fewer. The share of short-term separations is relatively stable between entry cohorts, as shown in Figure 3.A4.

Fifth, male household heads who migrate without their spouse typically have prior work experience. They are most commonly small traders and informal daily earners or salaried workers, and most have completed high-school education (Table 3.A2).

Finally, households experiencing separation differ in systematic ways from those that do not. Like the overall sample, most are concentrated in the small trader and informal daily earner category. However, they are more rural and somewhat larger in size, less represented among business owners, entrepreneurs, and formally qualified self-employed professionals, and slightly more likely to be engaged in salaried work (Table 3.A3).

3.4 Empirical Strategy

Our empirical strategy tracks household and individual outcomes during periods when the male household head is temporarily away. Given baseline differences between separating and non-separating households (sub-section 3.3.3), we first construct a matched control group to improve comparability. We then estimate effects using a difference-in-differences event study design that leverages the high-frequency structure of our panel data. This framework allows us to visualize dynamic patterns of adjustment before and after migration, including pre-trends and short- versus longer-term shifts in household behavior.

To strengthen causal inference, we exploit variation in migration driven by exogenous export demand shocks in manufacturing industries. These shocks influence the likelihood of male migration across districts and provide a source of plausibly exogenous variation in household separation.

A central concern is that these shocks may affect household outcomes through other local economic channels, potentially violating the exclusion restriction. Rather than isolating the effect of migration per se, we interpret our estimates as capturing household responses to migration episodes induced by labor pull shocks in tradable sectors. In this sense, our analysis provides a case study of how households adjust when male migration is triggered by exogenous labor market opportunities.

3.4.1 Constructing a Matched Control Group

As shown in Table 3.A3, households experiencing male-head migration differ systematically from those that do not. To improve comparability, we construct a matched control group prior to estimation. Treated households are matched to households that never experience a male or female separation event during 2014–2019, using baseline covariates as described in Appendix 3.A.5. From a pool of 213,594 eligible controls¹⁷, this

¹⁷We also exclude those households that observe a female household head separation as defined by us

procedure yields 9,134 matched households for 4,610 treated households. The resulting matched sample exhibits no statistically significant differences in baseline characteristics (Table 3.A4), ensuring that treated and control households are balanced on observables. All subsequent analyses are conducted on this matched sample.

3.4.2 Difference-in-differences estimator

To estimate dynamic treatment effects in settings with staggered adoption and treatment effect heterogeneity, we implement the estimator proposed by [de Chaisemartin and D’Haultfoeuille \(2023\)](#). In contrast to traditional two-way fixed effects (TWFE) models, which can produce biased estimates when treatment effects vary across units or time, this estimator constructs Difference-in-Differences (DID) comparisons at the group-time level, and aggregates them in a way that avoids negative weighting. Our implementation focuses on units that switch from untreated to treated or from joined households to separated households (“switchers-in”) and compares their outcome changes to those of units that remain untreated throughout the same period.

The basic building block of the estimator is the switcher-in DID at time period t , denoted $\text{DID}_{+,t}$. This term captures the average difference in outcome changes from $t-1$ to t between groups that enter treatment and those that remain untreated:

$$\text{DID}_{+,t} = \sum_{g: D_{g,t}=1, D_{g,t-1}=0} \frac{N_{g,t}}{N_{1,0,t}} (Y_{g,t} - Y_{g,t-1}) - \sum_{g: D_{g,t}=0, D_{g,t-1}=0} \frac{N_{g,t}}{N_{0,0,t}} (Y_{g,t} - Y_{g,t-1})$$

Here, $D_{g,t} \in \{0,1\}$ indicates whether group g is treated at time t , $Y_{g,t}$ is the average outcome of group g in period t , and $N_{g,t}$ is the number of units in that group. The first summation averages the pre/post outcome change for switchers-in (i.e., groups that move from untreated to treated between $t-1$ and t), while the second term does the same for control groups that remain untreated in both periods. Each group’s contribution is weighted by its size relative to the total number of units in its category, ensuring that the estimator reflects a weighted average across group-time comparisons.

To estimate dynamic treatment effects over event time, the estimator aligns switchers based on the timing of their first treatment and computes DID_ℓ for $\ell = 1, 2, \dots, L$, corresponding to the number of periods since the household head migrated. To ensure comparability across periods, we restrict the sample to switchers who remain observed over all relevant leads and lags. This avoids compositional bias due to panel attrition or irregular outcome availability. Each estimation has household and quadrimester fixed effects for household-level outcomes and individual and quadrimester fixed effects for individual-level outcomes. All estimations have standard errors clustered to the district level.

The identification of this estimator relies on two key assumptions. First, a parallel trends assumption: in the absence of treatment, the change in outcomes from $t-1$ to t for groups that enter treatment would have followed the same trend as the control groups that remain untreated. This assumption ensures that differences in pre/post changes between treated and untreated groups can be attributed to treatment rather than to differential trends. Second, the estimator assumes no interference across groups, a version of the Stable Unit Treatment Value Assumption (SUTVA). Formally, this implies that each group’s potential outcomes depend only on its own treatment status, and not on the treatment status of any other group ([de Chaisemartin and D’Haultfoeuille, 2023](#), Assumption 3). This rules out spillovers, general equilibrium effects, or any other form of cross-group interference.

A potential threat to the identification strategy arises from coincident demographic changes in the household at the time of household separation, particularly mortality

events. In our context, a non-negligible share of treated households experience the death of a household member at or near the time of migration by the household head. If such events affect consumption or other outcomes directly, and are correlated with treatment timing, they may violate the parallel trends assumption by inducing spurious jumps in outcomes concurrent with treatment. That is, some portion of the observed post-treatment change in outcomes could reflect endogenous demographic shocks rather than the causal impact of migration.

To address this concern, we implement two strategies. First, we include a control variable for household mortality to absorb direct level effects associated with death-related shocks. Second, we complement the DiD analysis with a shift-share instrumental variables (SSIV) approach, using a shift-share instrument based on exogenous labor-market pull shocks to isolate variation in the migration decision from origin push shocks.

3.4.3 Shift-Share Design

We employ a shift-share instrument, z_{iot} , to capture labor pull shocks arising from export commodity industries in migrant destination districts. Following the approach in [Madhok et al. \(2022\)](#), the instrument combines export price driven shocks at potential destinations (the shift) with household level measures of exposure to those shocks (the share).

This design identifies a set of complier households whose migration decisions respond to exogenous variation in labor demand and allows us to estimate the causal effects of migration episodes triggered by external economic opportunities. In doing so, we isolate a pull driven stream of migration that is plausibly orthogonal to household specific push factors at the origin.

The shift x_{dt} correspond to weighted export price shocks at destination district d , that emulate a labor pull shock. We construct it by multiplying the yearly export price fluctuations p_{jt} of the major export commodities j with each district's baseline exposure to those commodities. Specifically, we employ the 2010 district level export value of each commodity (v_{jd}) over the total baseline export value of each district (v_d) to capture the relative importance of each commodity within the district's export basket. These weighted price shocks are then summed across all commodities to generate an overall export demand shock for each district, and then multiplied by the total employment in the exporting industries in each district (emp_d) to generate an overall export demand shock for each district.

The export price fluctuations p_{jt} are the residual from autoregressive AR(1) process, capturing unanticipated commodity specific shocks net of trend and persistence.

$$x_{dt} = \frac{\sum_{j=1}^J p_{jt} \times v_{jd}}{v_d} \times emp_d \quad (3.21)$$

We employ two shares that measure the exposure to the pull labor shocks at destination.

The first share captures geographic exposure, reflecting the idea that labor pull shocks are stronger the closer they are to potential migrants. We employ a leave-one-out sum of all labor pull shocks x_{dt} to every potential destination district $d \in \Theta/o$, denoted as $\frac{1}{\tau_{od}}$. Here, Θ spans across all districts. It is weighted over the distance to each destination district τ_{od} .

$$s_{ot} = \sum_{d \in \Theta/o} \frac{x_{dt}}{\tau_{od}} \quad (3.22)$$

Section 3.3.3 discusses how geographical distance reduces the likelihood of migration, which provides evidence on distance as migration costs. Appendix 3.A.6 shows the geographical variation of the labor shocks at destination x_{dt} and the leave-one-out shock at

origin s_{ot} before and after residualizing for time and district fixed effects, which is part of our main specification.

The second share λ_i proxies the migration potential of the household. This is a propensity score constructed separately for male migrant-sending households and their matched control group, based on predetermined variables (household size, location, socioeconomic characteristics of the household head, etc.) at baseline. Appendix section 3.A.7 describes the construction of the propensity to migrate variable in detail.

Finally, we combine our shift and the share as follows

$$Z_{iot} = \underbrace{\lambda_{io}}_{\text{Share: Migration potential}} \times \underbrace{\sum_{d \in \Theta/o} \frac{1}{\tau_{od}}}_{\text{Share: Geographic exposure}} \times \underbrace{\frac{\sum_{j=1}^J p_{jt} \times v_{jd}}{v_d} \times \text{emp}_d}_{\text{Shift: Pull labor shock } x_{dt}} \quad (3.23)$$

where λ_{io} represents the baseline propensity of each household i , in the origin district o to migrate, s_{ot} represents the pull labor shock experienced at origin district o . x_{dt} represents the weighted export price shocks in the destination district $d \neq o$, and τ_{od} is the distance between the origin district o and the destination district d .

We apply the shift-share design at the annual level, allowing households time to adjust to export-driven labor demand shocks. The treatment variable, household separation, is 1 if the household remains separated for the complete year.

Instrument validity

The validity of our instrument relies on two key assumptions: (i) relevance, or the strength of the instrument in predicting household separation due to migration, and (ii) the exclusion restriction, which requires that the instrument affects household outcomes only through its impact on migration induced by exogenous labor demand shocks. We assess the first assumption in Section 3.A.8, where we document a strong first stage relationship between the instrument and household separation¹⁸.

To examine the exogeneity of the shocks, we compute Rotemberg weights in Section 3.A.10 to assess which destination cells contribute most to the identifying variation. This diagnostic helps detect whether our estimates are disproportionately influenced by a small number of large or volatile shocks, and whether those shocks originate in locations that differ systematically in ways that may threaten validity. Table 3.A7 shows that no single district dominates the instrument. The largest district receives 2.7% of the total weight, and the top fifteen districts together account for about 24%. Overall, the pattern suggests no undue concentration of identifying variation, supporting the exogeneity assumption.

A further concern in shift-share designs is the potential endogeneity of the “share” component. As highlighted by Madhok et al. (2022), if household-specific migration propensities (λ_{io}) or geographic exposure weights (e.g., inverse distance to destinations) are correlated with the “shift” component, bias may arise even when destination shocks are exogenous. To address this, we test for balance in pre-treatment outcomes and migration propensities across bins of predicted treatment intensity, following the approach of Goldsmith-Pinkham, Sorkin, and Swift (Goldsmith-Pinkham et al.) in Section 3.A.11.

Finally, a key threat to the exclusion restriction arises from general equilibrium effects. If labor demand shocks in destination districts influence economic conditions in origin districts via remittances, changes in local wages, or demand for local services then household outcomes may respond directly to the shocks, not just through migration. To probe this possibility, we estimate balance tests for the inverse-distance weighted pull shocks s_{ot} on outcomes in households not differentially exposed to migration in Section

¹⁸We also discuss the characteristics of compliers in Section 3.A.9

3.A.12. While we find no systematic effects on non-migrant households, we cannot fully rule out spillovers. We thus interpret our estimates as capturing the overall household response to separation episodes driven by exogenous labor market opportunities, rather than isolating the pure effect of migration.

Taken together, the difference-in-differences and SSIV estimates offer a more complete view of migration dynamics to one shaped by household specific conditions, and another driven by exogenous labor demand shocks.

Two-stage least squares

To estimate the causal impact of migration on household level reallocation of labor and capital, we adopt a standard two-stage least squares (2SLS) framework. Specifically, we instrument for male household head migration using a shift-share measure of exposure to labor demand shocks:

$$\text{Mig}_{iot} = \mu_1 \underbrace{\lambda_{io}s_{ot}}_{z_{iot}} + \mu_2 s_{ot} + \mu_3 x_{ot} + \alpha_i + \gamma_t + v_{iot} \quad (3.24)$$

$$Y_{iot} = \beta_1 \widehat{\text{Mig}}_{iot} + \beta_2 s_{ot} + \beta_3 x_{ot} + \alpha_i + \gamma_t + \epsilon_{iot} \quad (3.25)$$

In the first stage (Equation 3.24), household separation due to unaccompanied male household head migration Mig_{iot} is instrumented using $z_{iot} = \lambda_{io}s_{ot}$, where λ_{io} is the household's baseline propensity to migrate and s_{ot} is the inverse-distance weighted labor pull shock experienced at the origin. The term x_{ot} denotes the direct export price shock in the origin district, included to address potential spatial correlation between destination and origin shocks. α_i and γ_t denote household and time fixed effects, respectively. To the extent that z_{iot} is orthogonal to unobserved drivers of migration and outcomes conditional on controls and fixed effects, $\widehat{\text{Mig}}_{iot}$ isolates variation in migration induced by exogenous shifts in destination labor demand.

In the second stage (Equation 3.25), we examine how instrumented migration affects household outcomes Y_{iot} , such as labor allocation, income, or investment. By conditioning on s_{ot} and x_{ot} , we account for both direct exposure to labor demand and local economic conditions in the origin district.

Controls for outcomes at the household level include household fixed effects and year fixed effects. Controls for outcomes at the individual level include individual fixed effects, year fixed effects, and controls for age and age squared.

It is important to emphasize that the instrumental variable approach identifies a Local Average Treatment Effect (LATE) for complier households whose migration decisions respond to exogenous labor demand shocks. This estimate reflects the average effect of separation across all periods during which the household head is away and is unaccompanied by a spouse, without distinguishing between short- or long-term separations, or the timing of those events. As a result, it may mask heterogeneity in effects by duration of separation or by time since migration.

3.4.4 Return Migration

We estimate the effects of return migration among households where the male household head reunites with the family during the observation period (2014–2019). Since nearly half of the treated households experience reunification within this window, as seen in Table 3.A1, we adapt the difference-in-differences estimation strategy to explore these dynamics with the largest sample we can utilize.

Specifically, we relax the balanced panel requirement across pre- and post-return periods to increase the sample size. This means we pool treatment effects across households

that reunify for only a single quadrimester as well as those that remain together thereafter for longer periods. Our primary focus is on the immediate period following reunification ($t+1$), where statistical power is highest.

We estimate effects by comparing households that experience return migration to those that remain separated over the same horizon. This comparison excludes the never-separated control group; our interest here is not in evaluating the effect of separation per se, but in understanding the consequences of return conditional on prior separation.

3.5 Result and Discussion

This section presents our main results. We first describe demographic patterns around the household head's migration. We then show how migration changes income, labor supply, and assets using an event study, and a shift share IV shows a similar pattern. Next we report what happens at return. For each outcome we also show results by baseline income and by location. Additional tables and checks are reported the Appendix. The interpretation of these results is guided by the conceptual framework introduced in Section 3.2, which characterizes household responses to the onset of migration-induced separation.

3.5.1 Household Separation Coincides with Demographic Changes within the Household

Household separation due to male household head migration is sometimes preceded or followed by a demographic shock, as shown in Figure 3.B11. The probability that a working-age household member dies within the first eight months of separation is 6 percentage points higher than in treated households. Similarly, the likelihood that a household member over 60 years old dies within the two quadrimesters preceding separation is 1 percentage point higher. These effects are driven by male household members, as shown in Table 3.B12. These patterns raise concerns that migration may be endogenous to negative household events, either anticipatory (e.g., due to illness) or reactive (e.g., after the death of an elderly member).

Although the incidence of these shocks is relatively low, we include a control for household mortality to address potential bias in our difference-in-differences estimates¹⁹. To further mitigate endogeneity concerns, we implement an instrumental variable strategy that leverages variation in migration induced by labor pull shocks in the manufacturing sector.

3.5.2 Other Members Migrate with the Male Household Head

The migration of other household members frequently coincides with, or follows, the migration of the male household head. We estimate an average increase of 1.23 migrants in

¹⁹We identify that, among the 4,610 households experiencing separation, 333 report the loss of a household member within the first year following the male household head's migration. Of these, 104 involve the death of a female member. Table 3.A10 shows that households experiencing such demographic shocks do not differ substantially from the broader treatment sample along most observable characteristics. The primary distinction is geographic: these households are disproportionately located in large urban areas. Additionally, Table 3.B13 shows that the instrumental variable strategy does not have any positive significant effect on household mortality as observed in the difference-in-differences estimates. This suggests that migration in response to labor pull shocks is not driven by adverse household events, but rather by external economic opportunities.

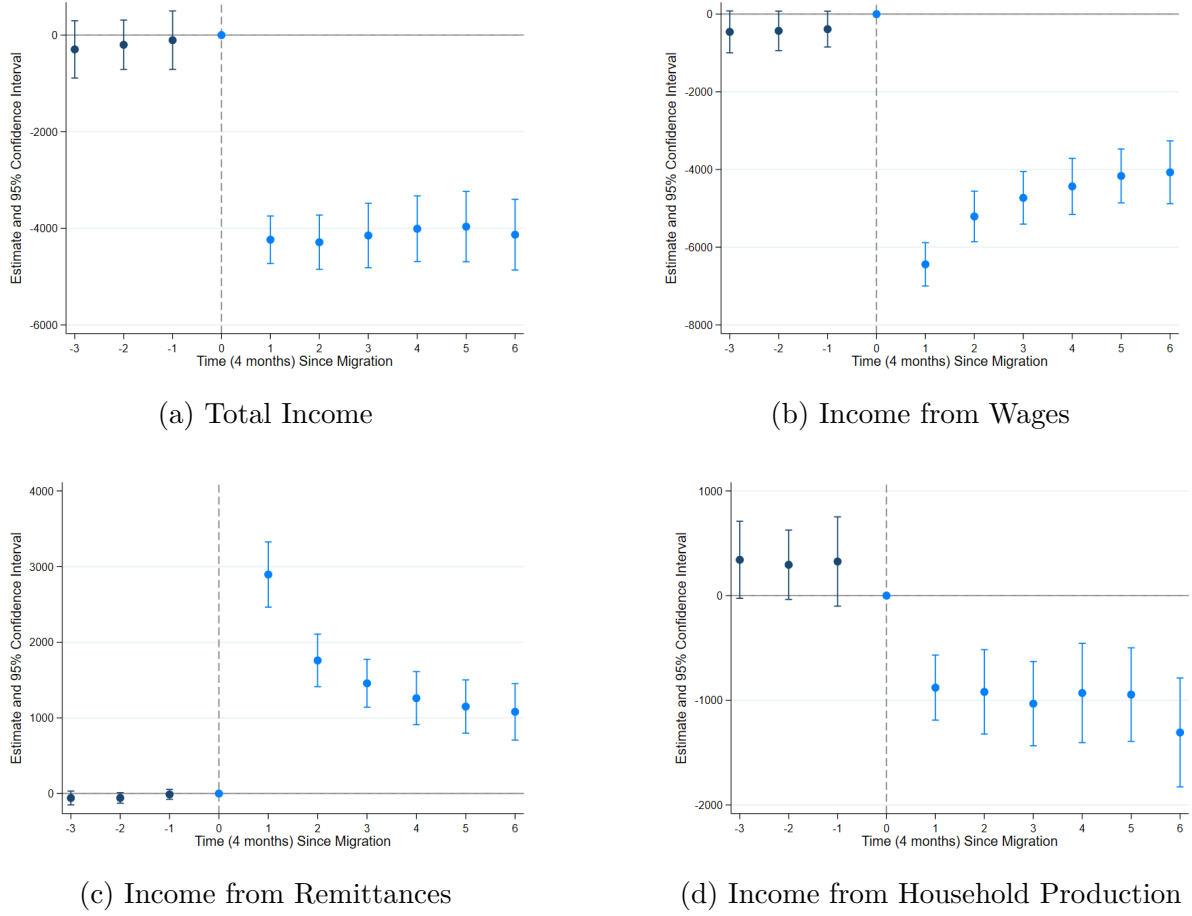
the first quadrimester, which implies an increase of 0.23 migrants that is not the household head. This increase is primarily driven by accompanied children under the age of 18, which increase is 0.185 in the first quadrimester. The migration of these accompanying members is not transient, rather, it persists over time as seen in Figure 3.B12

3.5.3 Income Composition Shifts: Wage Losses and Remittance Substitution

During the period of separation, when the household head is away, total household income declines sharply (Figure 3.1). In the first quadrimester following migration, average household income falls by Rs. 4,767, driven primarily by the loss of wage earnings. Wage income drops by Rs. 6,026, reflecting the departure of the primary earner. This reduction is only partially offset by an average increase of Rs. 2,467 in remittances sent by the migrant. Income from household production also falls by Rs. 1,246, suggesting a contraction in self-employment or farm-based activities. These shifts in income composition persist across subsequent waves, indicating a sustained reallocation from wage labor to remittances during the migrant's absence. This net income shortfall at origin is a central feature of the conceptual framework and constitutes the primary mechanism triggering household reallocation responses at the onset of separation.

SSIV estimates (Table 3.1) mirror this pattern, though the remittance gains are smaller in magnitude, reinforcing the conclusion that remittances only partially cushion the loss of local earnings.

Figure 3.1: Household Income



Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. The sample comprises households that experienced separation for six consecutive periods (two years) between 2015 and 2017. Estimates compare outcome changes for groups that transition from untreated to treated status at event time 1 to those that remain untreated over the same period, using the period immediately before separation as the baseline. The specification includes household and quadrimester fixed effects, and a time-varying control for household mortality. Standard errors are clustered at the treatment location. The dependent variable is the monthly household income from each source. Table 3.B16 details the coefficients shown in the figures.

Table 3.1: Second Stage: Household Income

	(1)	(2)	(3)	(4)
	Total income	Wages	Remittances	HH Production
$\hat{Mig}_{iot}$	-5826.2*** (1857.6)	-5337.3*** (1831.1)	770.4** (319.7)	-1217.5 (1299.1)
Outcome Mean	18232.4	13282.6	538.5	3113.3
KP (F-stat)	287.3	287.3	287.3	287.3
Treated Households	4610	4610	4610	4610
Observations	75375	75375	75375	75375

Notes: Mig_{iot} indicates if the household is separated in year t due to the migration of the male household head at time t in district origin o instrumented by labor pull shock from exporting industries in destination districts. The dependent variable in Column (1) is the total monthly income earned by the household at the origin. Column (2) reports total monthly wages earned by household members. Column (3) captures total remittances and private transfers received by the household at the origin. Column (4) measures total income from household production or business activities. All regressions include household and year fixed effects. Standard errors are clustered at the district level and reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

While total income falls, the implications for household well-being also depend on changes in income per capita, which we examine next. In per capita terms (Figure 3.B13), the initial decline in wage income is sharp but shows signs of modest recovery over time,

likely reflecting increased labor market participation by other household members. Remittance inflows rise steadily and help offset much of the wage loss. Income from household production remains relatively depressed throughout, suggesting a diminished role for farming or home enterprises as sources of income during separation. The SSIV estimates (Table 3.B22) reinforce this pattern: while remittances per capita increase significantly, they do not fully compensate for lost wage income, and total income per capita remains negative, though insignificantly so.

These muted average effects raise an important question: if income retained at the origin household remains broadly unchanged on average, who gains and who loses from migration? To examine this, we stratify the sample by deciles of baseline per capita income, measured in the period prior to separation for treated households and the corresponding period for matched controls, and estimate the effect at $t+1$. To maximize sample size, we relax the requirement of observing households together for four quadrimesters and separated for six.

Figure 3.B14 shows that households in the lower deciles experience net gains in per capita income following migration, as modest wage losses are more than offset by remittances. In contrast, wealthier households face larger declines in wage income that are only partially compensated, resulting in net losses. These findings resonate with prior research on migration and risk-sharing by Morten (2013) which emphasizes that the distributional consequences of migration may differ depending on household characteristics.

Although the migrant's earnings at the destination are not observed, these findings raise an important question: if income retained at home falls, particularly for higher income households, why do they still undertake temporary migration? To explore these dynamics, we next examine how labor supply, schooling, and asset ownership evolve over the migration cycle.

3.5.4 Spouse Labor Market Participation Increases During Separation

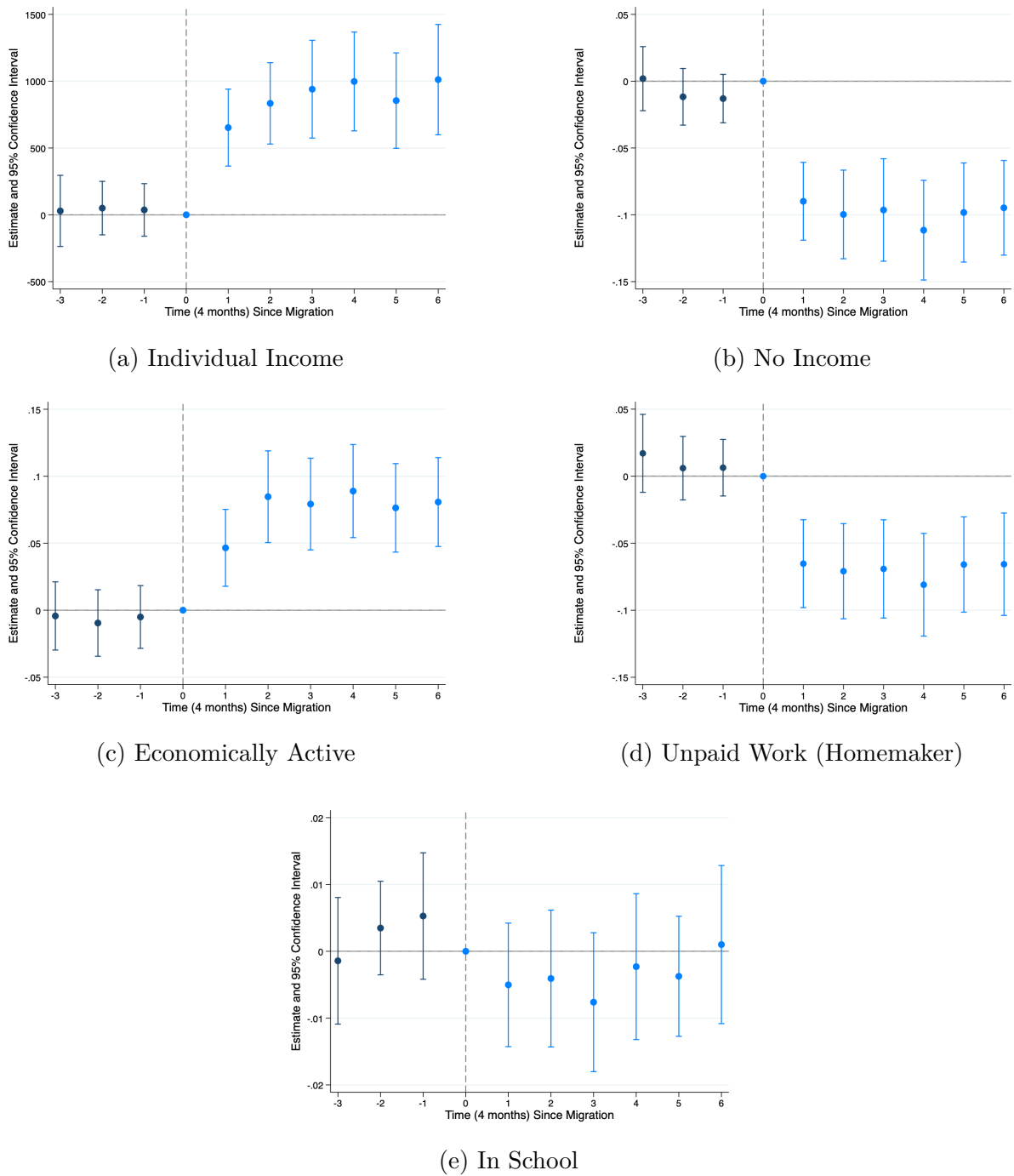
The conceptual framework predicts that, at the onset of migration-induced separation, the female spouse increases market labor supply as the loss of male wage income raises the opportunity cost of home production (Proposition 1, Section 3.2.3). In empirical results we find that in the absence of the male household head, spouses remaining at home substantially increase their participation in the labor market, in line with the prediction. Figure 3.2 shows that at $t+1$, the share of spouses who are economically active (working or actively seeking work) rises by 4.7 percentage points, while the share identifying as “homemakers” falls by 6.7 percentage points, and the share with no income declines by 9 percentage points. Correspondingly, average monthly individual income increases by Rs. 652. These effects persist and grow over time. There is no meaningful change in the share of spouses who are students.

SSIV estimates in Table 3.2 confirm this reallocation. One year after separation, the share of spouses economically active throughout the year increases by 44 percentage points. The share with zero income declines by 65 percentage points, while the share reporting homemaker status throughout the year falls by 71 percentage points. The share identified as students falls by 8 percentage points.

Spouses also diversify into a broad range of occupations. Figure 3.3 shows increases in work as farmers, entrepreneurs, and informal workers. However, the occupational shifts vary significantly by baseline income and location. As shown in Figure 3.B15, spouses in poorer households are more likely to enter farming and informal work. There is no clear evidence of a rise in salaried or entrepreneurial work across the income distribution.

Figure 3.B17 further shows that farming occupations are primarily taken up by rural spouses, while entrepreneurial roles are concentrated among urban spouses.

Figure 3.2: Spouse's Economic Activity



Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot reports dynamic treatment effects using the sample selection and control group from Figure 3.1. Panel A presents monthly individual income (in rupees). Panel B reports whether the spouse has zero individual income. Panel C shows an indicator for whether the spouse is economically active (working or unemployed and seeking work). Panel D shows an indicator for whether the spouse is engaged in unpaid work i.e. her main occupation is “homemaker.” Panel E shows an indicator for student status as the spouse’s main occupation. Table 3.B23 details the coefficients and controls shown in the figures.

Table 3.2: Second Stage: Spouse's Economic Activity

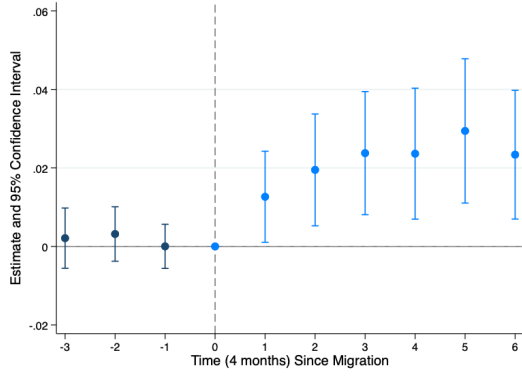
	(1)	(2)	(3)	(4)	(5)
	Individual Income	No Income	Economically Active	Unpaid Work	In School
$\hat{Mig}_{iot}$	1199.0 (935.3)	-0.646*** (0.215)	0.445*** (0.0949)	-0.708*** (0.209)	-0.0808** (0.0393)
Outcome Mean	810.5	0.553	0.100	0.537	0.0252
KP (F-stat)	77.00	77.00	77.00	77.00	77.00
Treated Households	2623	2623	2623	2623	2623
Observations	87967	87967	87967	87967	87967

Notes: M_{iot} indicates if the individual is in a household that is separated in year t due to the migration of the male household head in district origin o instrumented by labor pull shock from exporting industries in destination districts. The dependent variable in Column (1) is the monthly income earned (in rupees). In Column (2) is an indicator if the income is zero throughout the year. In Column (3) is an indicator if the member is working or not working but looking for a job for at least one quadrimester. In Column (4) is an indicator if the member's occupation is "home maker" throughout the year. In Column (5) if the member's occupation is "student" for at least one quadrimester. All regressions include individual and year fixed effects. Standard errors are clustered at the district level and reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

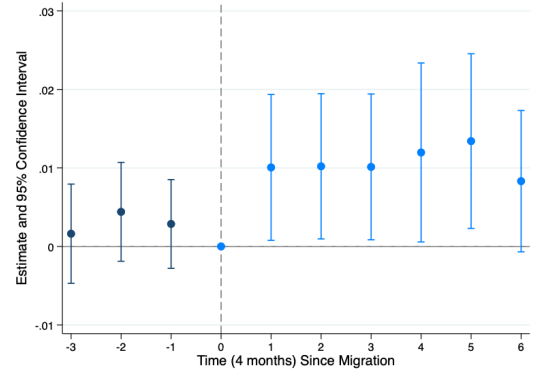
The SSIV estimates as shown in Table 3.3 do not allow identification of specific occupational categories but do reveal a sharp decline in the residual "other" category, comprising homemakers, retirees, and students.

Importantly, these labor market responses are concentrated in the lower part of the income distribution. As Table 3.B15 shows, spouses from wealthier households show limited increases in income or activity. Similarly, Figure 3.B17 suggests stronger earnings responses among urban spouses. Together, these findings suggest that migration-induced labor substitution at home is most pronounced among poorer and urban households, consistent with Proposition 1 of the conceptual framework, which predicts an increase in female labor supply following a reduction in male earnings at origin.

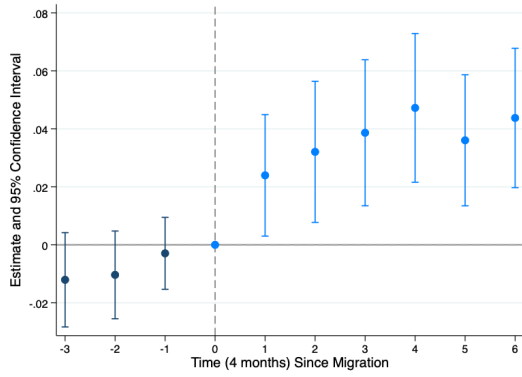
Figure 3.3: Spouse's Occupation



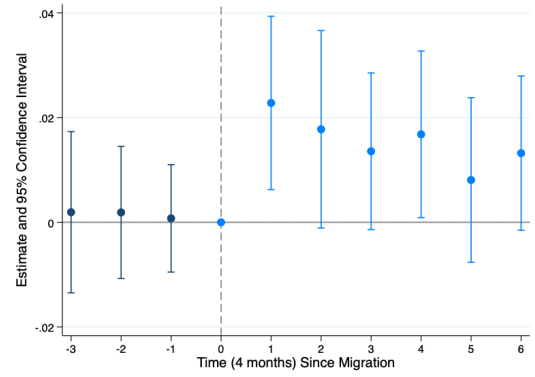
(a) Business/Entrepreneur



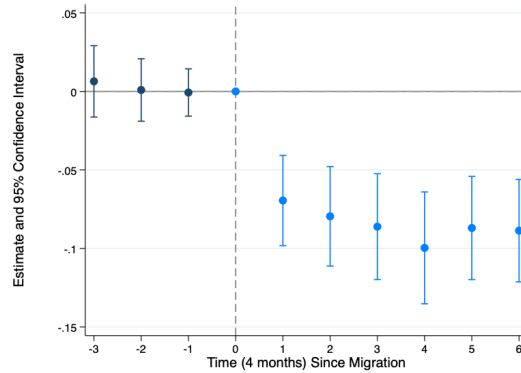
(b) Farmer



(c) Small trader or Informal worker



(d) Salaried/White collar workers



(e) Other

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot reports dynamic treatment effects using the sample selection and control group from Figure 3.1. Panel A shows an indicator for whether the spouse occupation is a business person or entrepreneur, including business employees, entrepreneurs, qualified self-employed professionals, self-employed professionals and self-employed entrepreneurs. Panel B dependent variable is an indicator if the spouse's occupation is farmer, including organized farmers or small/marginal farmers. Panel C corresponds to the occupation of small trader and informal workers, including informal daily wage earners, home-based workers, hawkers, agricultural laborers, and wage laborers. Panel D corresponds to salaried employees including managers/supervisors, white-collar professional employees, white-collar clerical employees, non-industrial technical employees, industrial workers, support staff and legislators/social workers/activists. Panel E corresponds to other occupations including retirees, students and home makers. Table 3.B24 details the coefficients and controls shown in the figures.

Table 3.3: Second Stage: Spouse's Occupation

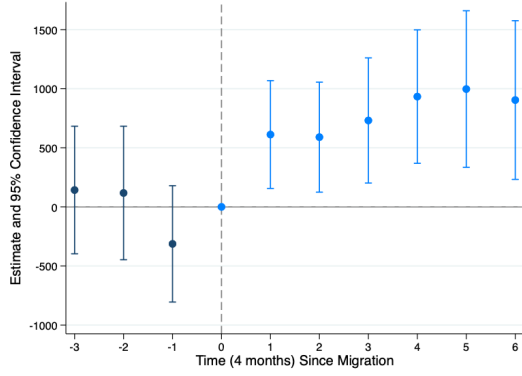
	(1)	(2)	(3)	(4)	(5)
	Business Entrepreneur	Salaried or White Collar Professional	Farmer	Small Trader & Informal Worker	Other
$\hat{Mig}_{iot}$	0.0510 (0.0434)	-0.0752 (0.0651)	0.0188 (0.0391)	-0.00794 (0.0801)	-0.734*** (0.213)
Outcome Mean	0.0170	0.0491	0.0140	0.0648	0.567
KP (F-stat)	77.00	77.00	77.00	77.00	77.00
Treated Households	2623	2623	2623	2623	2623
Observations	87967	87967	87967	87967	87967

Notes: Mig_{iot} indicates if the individual is in a household that is separated in year t due to the migration of the male household head in district origin o instrumented by labor pull shock from exporting industries in destination districts. The dependent variable in Column (1) indicates whether the spouse's occupation is a business person or entrepreneur. Column (2) corresponds to salaried employees or white-collar professionals. Column (3) indicates if the spouse is a farmer. Column (4) includes small traders and informal workers. Column (5) includes retirees, students, and homemakers. All regressions include individual and year fixed effects. Standard errors are clustered at the district level and reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

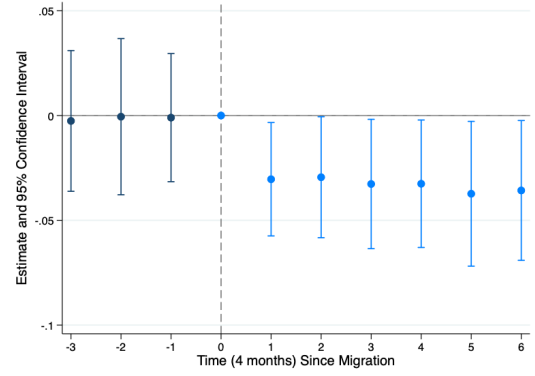
3.5.5 Working-age Household Members Increase Labor Participation at the Expense of Education

The conceptual framework further predicts that young adults increase labor supply in response to the household income shortfall created by migration (Proposition 2, Section 3.2.3), with schooling adjusting as the residual use of time (Proposition 3, Section 3.2.3). As shown in Figure 3.4, working-age males become more economically engaged in the separation period. Their labor force participation increases by 3.2 percentage points, individual income rises by Rs. 612 per month, and the share with no income declines by 3 percentage points. These gains appear to come mainly at the expense of education: the share of male members reporting "student" as their main occupation falls by 3.3 percentage points. In other words, migration prompts younger men to enter the labor force at the expense of continued education, as schooling is defined as the residual from the time constraint in the model, consistent with Proposition 3.

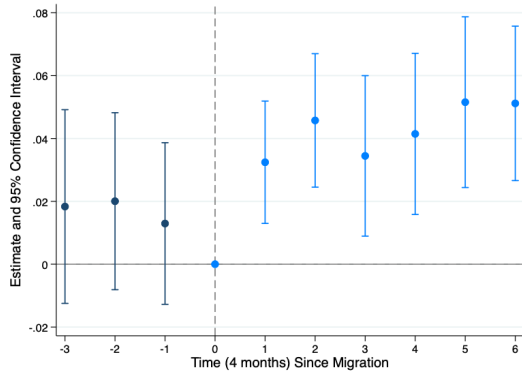
Figure 3.4: Working-age Male's Economic Activity



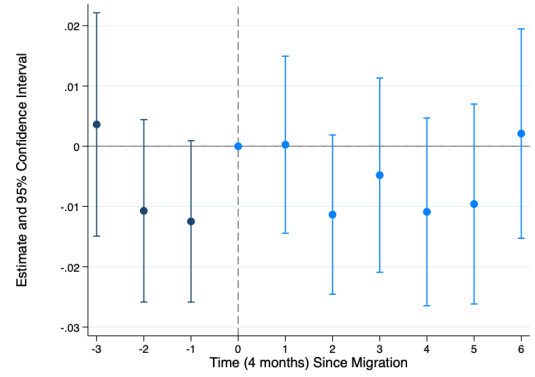
(a) Individual income



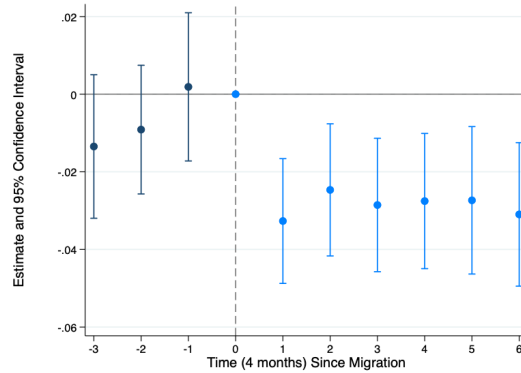
(b) No income



(c) Economically Active



(d) Unpaid Work (Homemaker)



(e) In School

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot reports dynamic treatment effects using the sample selection and control group from Figure 3.1. Panel A presents monthly individual income (in rupees). Panel B reports whether the member has zero individual income. Panel C shows an indicator for whether the member is economically active (working or unemployed and seeking work). Panel D shows an indicator for whether the member is engaged in unpaid work i.e. her main occupation is “homemaker.” Panel E shows an indicator for student status as the members’s main occupation. Table 3.B25 details the coefficients and controls shown in the figures.

Table 3.4: Second Stage: Working-age Male's Economic Activity

	(1)	(2)	(3)	(4)	(5)
	Individual Income	No Income	Economically Active	Unpaid Work	In School
$\hat{Mig}_{iot}$	733.9 (2699.5)	-0.0387 (0.183)	0.160 (0.112)	0.0415 (0.0458)	-0.164 (0.119)
Outcome Mean	3697.9	0.356	0.297	0.0161	0.397
KP (F-stat)	78.56	78.56	78.56	78.56	78.56
Treated Households	21354	21354	21354	21354	21354
Observations	114546	114549	114549	114549	114549

Notes: Mig_{iot} indicates if the individual is in a household that is separated in year t due to the migration of the male household head in district origin o instrumented by labor pull shock from exporting industries in destination districts. The dependent variable in Column (1) is the monthly income earned (in rupees). In Column (2) is an indicator if the income is zero. In Column (3) is an indicator if the member is working or not working but looking for a job. In Column (4) is an indicator if the member's occupation is "home maker". In Column (5) if the member's occupation is "student". All regressions include individual and year fixed effects. Standard errors are clustered at the district level and reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

SSIV estimates (Table 3.4) confirm the same directional effects i.e. greater labor participation, rising income, and falling inactivity, but the magnitudes are smaller and statistically insignificant. However, we find no significant shifts in the type of work undertaken. As shown in 3.B18, the occupational composition of working-age males remains largely unchanged.

Among working-age female household members, we also observe increases in labor participation along with a reduction in student status (Figure 3.5). Yet, the number of eligible observations is small, as few non-spouse female members are present and continuously observed post-separation. This limits our ability to detect sharp effects. The corresponding SSIV estimates in Table 3.5 show positive but imprecisely estimated effects on female income²⁰.

Table 3.5: Second Stage: Working-age Female's Economic Activity

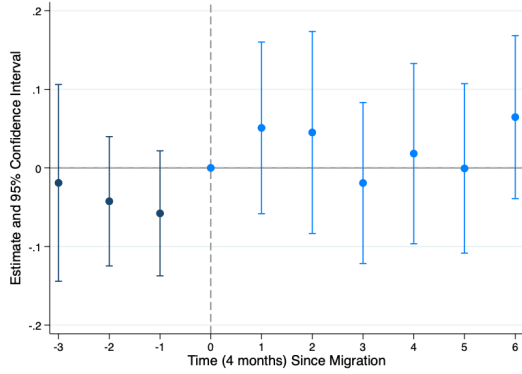
	(1)	(2)	(3)	(4)	(5)
	Individual Income	No Income	Economically Active	Unpaid Work	In School
$\hat{Mig}_{iot}$	9384.4* (5268.1)	-2.361* (1.283)	-0.370 (0.415)	-0.218 (0.556)	-0.738 (0.580)
Outcome Mean	3697.9	0.356	0.297	0.0161	0.397
KP (F-stat)	8.949	8.949	8.949	8.949	8.949
Treated Households	21354	21354	21354	21354	21354
Observations	12920	12920	12920	12920	12920

Notes: Mig_{iot} indicates if the individual is in a household that is separated in year t due to the migration of the male household head at time t in district origin o instrumented by labor pull shock from exporting industries in destination districts. The dependent variable in Column (1) is the monthly income earned (in rupees). In Column (2) is an indicator if the income is zero. In Column (3) is an indicator if the member is working or not working but looking for a job. In Column (4) is an indicator if the member's occupation is "home maker". In Column (5) if the member's occupation is "student". All regressions include individual and year fixed effects. Standard errors are clustered at the district level and reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

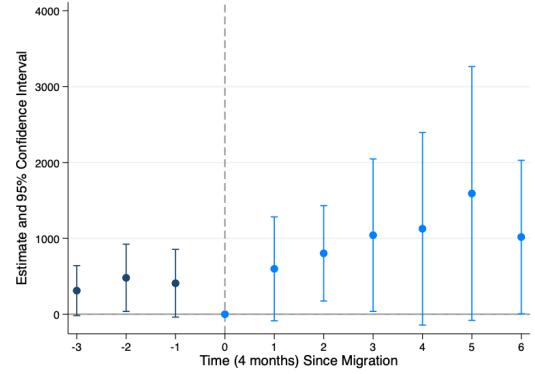
Finally, we explore heterogeneity by baseline income and find no consistent pattern across income deciles. The only robust difference is that individual income gains among

²⁰Figure 3.B19 suggests that when women do take up work, they primarily enter farming or salaried/white-collar occupations. However, statistical power is limited, and estimates should be interpreted with caution.

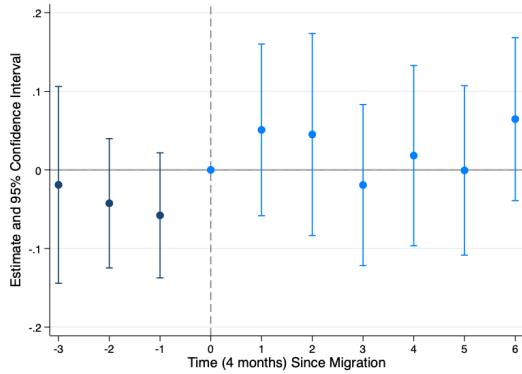
Figure 3.5: Working-age Female's Economic Activity



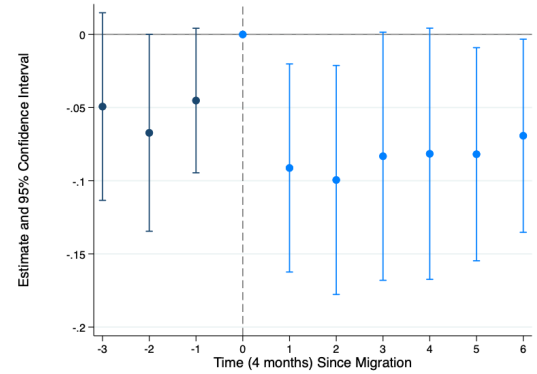
(a) Economically Active



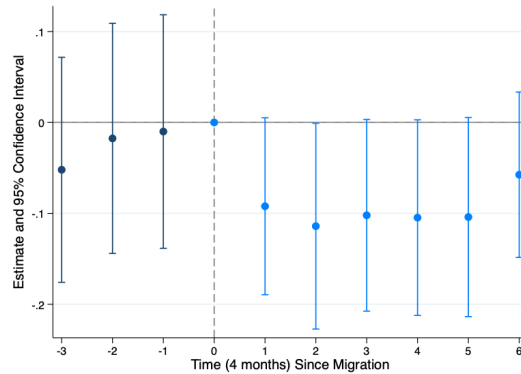
(b) Individual income



(c) Unpaid Work (Homemaker)



(d) No income



(e) In School

Notes: Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot reports dynamic treatment effects using the sample selection and control group from Figure 3.1. Panel A presents monthly individual income (in rupees). Panel B reports whether the member has zero individual income. Panel C shows an indicator for whether the member is economically active (working or unemployed and seeking work). Panel D shows an indicator for whether the member is engaged in unpaid work i.e. her main occupation is “homemaker.” Panel E shows an indicator for student status as the members’ main occupation. Table 3.B27 details the coefficients and controls shown in the figures.

male members are concentrated outside the top deciles (Figure 3.B20). Taken together, these results suggest that separation reallocates household resources by drawing younger men into work and reducing school attendance, with smaller and less precisely measured effects on non-spouse female members.

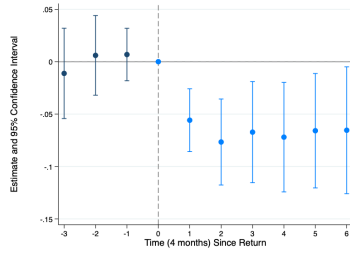
3.5.6 Loss of Productive Assets Following Migration

Temporary male migration leads to clear and persistent reductions in household asset ownership, particularly for high-value durables and productive assets. Asset dynamics fall outside the scope of the static conceptual framework and are therefore examined empirically to assess whether temporary migration shocks generate persistent changes in household portfolios. Figure 3.6 shows that two-wheelers exhibit the sharpest decline, suggesting that these may be taken by the migrant to the destination or liquidated. Declines are also observed for cars, refrigerators, computers, tractors and cattle. The household asset index, falls steadily over time, largely driven by these durable losses. This pattern mirrors the findings in Madhok et al. (2022), who reports reduced agricultural investment among migrant households, and aligns with our earlier evidence on falling farm income.

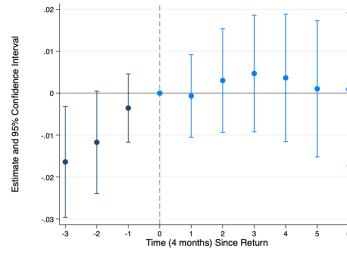
Further, to examine distributional effects Figure 3.B21 plots cumulative asset changes from $t + 1$ to $t + 6$ by baseline income decile. We observe sharp and consistent declines among higher income households, particularly for computers, cars, and two wheelers. In contrast, lower income households exhibit relatively flat trends, with no clear declines across asset types.

Figure 3.6: Household assets

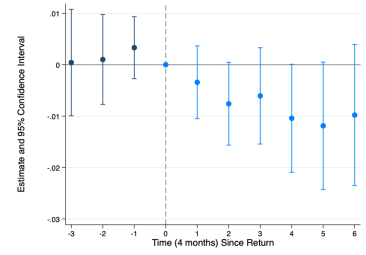
Asset Index and Appliances



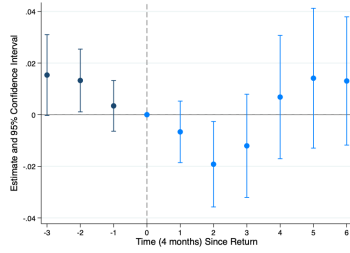
(a) Asset Index



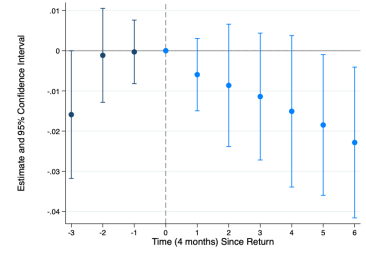
(b) Washing Machine



(c) Computers

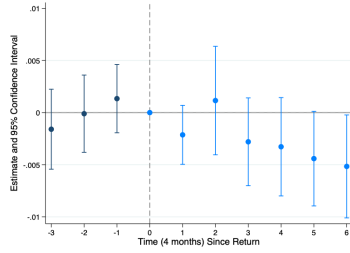


(d) Coolers

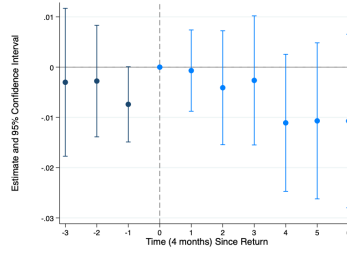


(e) Refrigerators

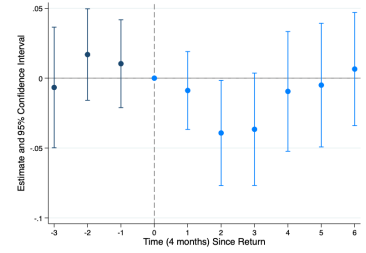
Productive Assets



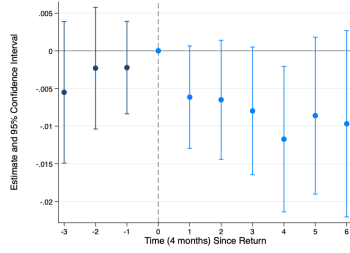
(f) Tractors



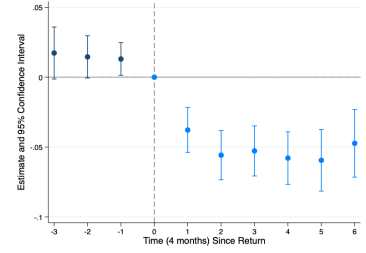
(g) Generators



(h) Cattle



(i) Cars



(j) Two wheelers

Notes:Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. The asset index in Panel A is a continuous measure constructed using principal component analysis (PCA) of binary asset ownership indicators. All other panels show binary indicators for ownership of specific assets: washing machines, computers, coolers, refrigerators (Panels B–E), and productive assets including tractors, generators, cattle, cars, and two-wheelers (Panels F–J). Tables 3.B29 and 3.B30, details the coefficients and controls used in this figure.

Finally, SSIV estimates in Table 3.6 reinforce these patterns, most coefficients are negative, and effects on two-wheelers and refrigerators are significant. Overall, migration leads to partial household decapitalization, particularly of durables, reflecting both coping

strategies during separation and potential shifts in intra-household resource allocation.

Table 3.6: Household Assets

Panel A: Assets Index and Appliances

	(1)	(2)	(3)	(4)	(5)
	Asset Index	Washing	Computers	Coolers	Refrigerator
$\hat{\text{Mig}}_{iot}$	-0.417*** (0.115)	-0.0434 (0.0595)	-0.0550 (0.0359)	-0.0403 (0.0679)	-0.0974* (0.0540)
Outcome Mean	0.711	0.278	0.0956	0.479	0.569
KP (F-stat)	287.9	287.9	287.9	287.9	287.9
Treated Households	4610	4610	4610	4610	4610
Observations	75346	75346	75346	75346	75346

Panel B: Productive Assets

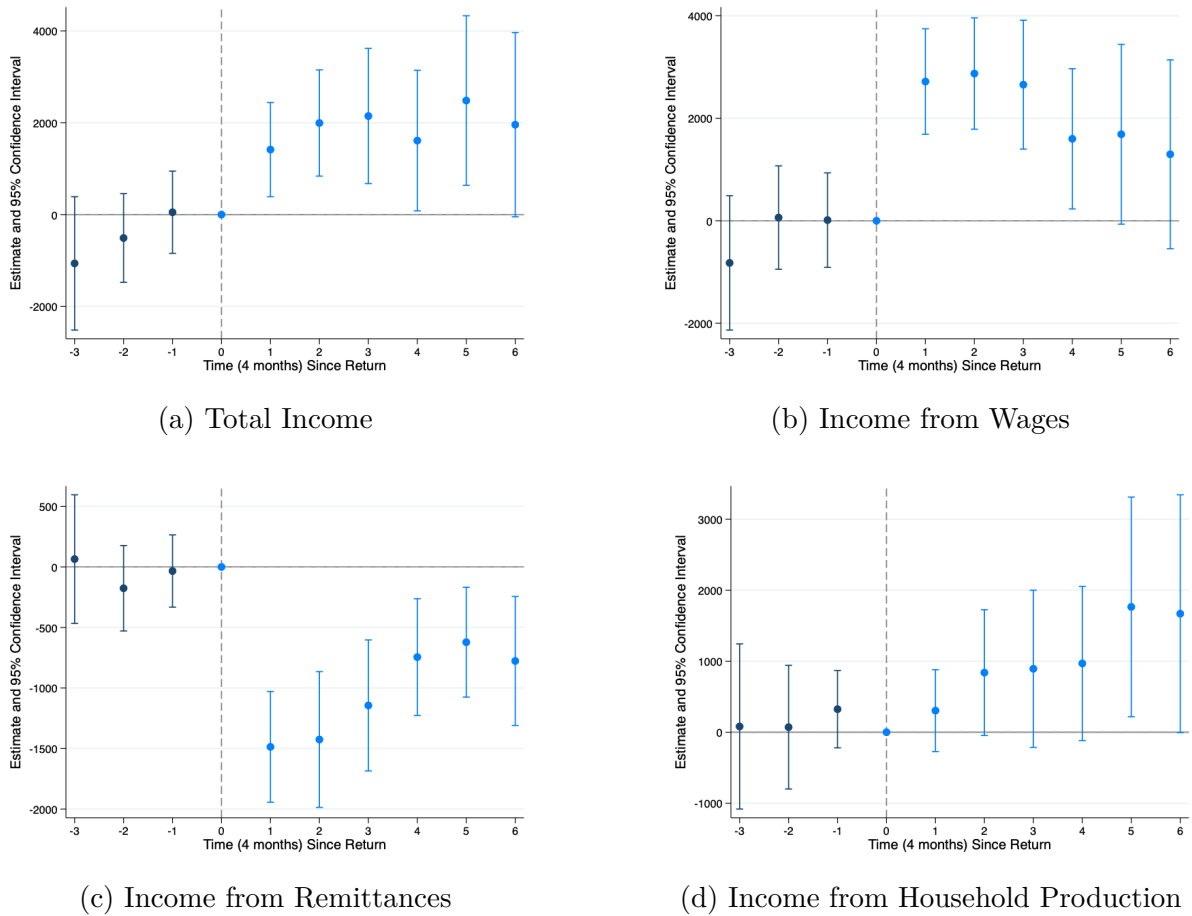
	(1)	(2)	(3)	(4)	(5)
	Tractors	Cattle	Generator	Cars	Two wheelers
$\hat{\text{Mig}}_{iot}$	-0.000279 (0.0132)	-0.221 (0.166)	-0.0736 (0.0481)	-0.0207 (0.0355)	-0.298*** (0.0652)
Outcome Mean	0.0165	0.514	0.224	0.0868	0.658
KP (F-stat)	287.9	287.9	287.9	287.9	287.9
Treated Households	4610	4610	4610	4610	4610
Observations	75346	75346	75346	75346	75346

Notes: $\hat{\text{Mig}}_{iot}$ indicates if the household is separated in year t due to the migration of the male household head in district origin o , instrumented using labor pull shocks from exporting industries in destination districts. Panel A reports effects on an asset index (Column 1), constructed using principal component analysis (PCA) of household ownership of consumer durables, and on binary indicators for ownership of appliances (Columns 2–5). Panel B reports effects on binary indicators for ownership of productive assets (Columns 1–5), including tractors, cattle, generators, cars, and two-wheelers. All regressions include household and year fixed effects. Standard errors are clustered at the district level and reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3.5.7 Short-Term Reversals and Persistent Shifts after Migrant Returns

While the conceptual framework focuses on household adjustment at the onset of separation, the high-frequency data allow us to document the extent to which these responses reverse or persist following reunification. We implement the difference-in-differences approach in Section 3.4.4 to examine household dynamics following the return of the migrant household head. Specifically, we estimate effects by comparing households that experience return migration to those that remain separated over the same horizon. This analysis focuses on the within-treated variation and excludes the never-separated control group, allowing us to isolate changes associated with reunification rather than initial separation.

Figure 3.7: Household Income after the Migrant Returns



Notes: Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This figure represents household income after the return of the male migrant household head. Panel A presents monthly total income (in rupees). Panel B reports total income from wages. Panel C shows total income from remittances. Panel D shows total income from household production. Table 3.B31 details the coefficients and controls shown in the figures.

Figure 3.7 shows that total household income rises after return, driven almost entirely by renewed wage earnings. This increase is offset by the collapse of remittances and only a modest rebound in household production, which does not recover to pre-separation levels. As a result, when adjusted for household size, there is no significant change in per capita income (Figure 3.B22), underscoring that reunification shifts the composition of income without delivering clear welfare gains to the origin household.

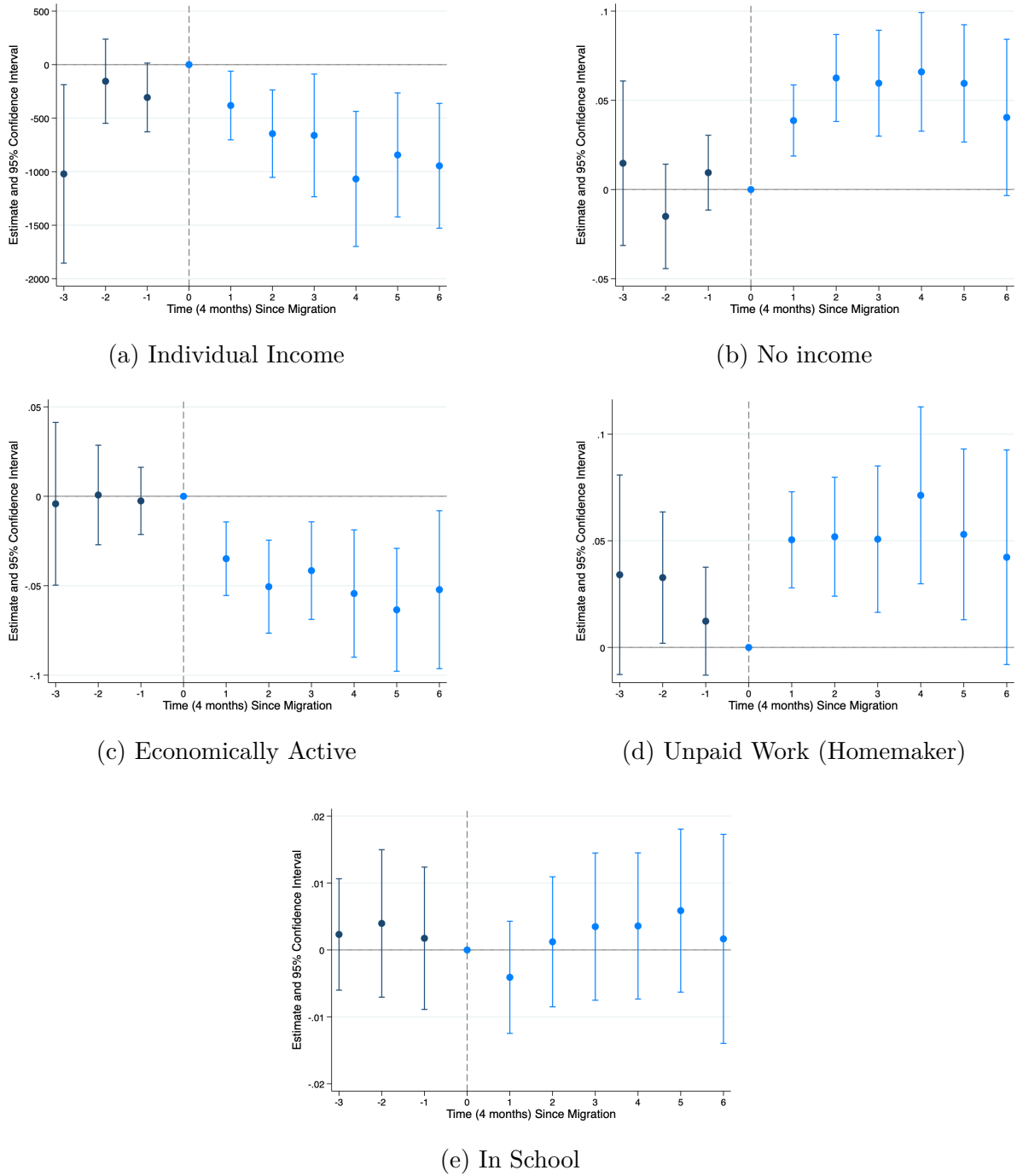
Figure 3.8 shows that the labor supply adjustments of the spouse during separation largely reverse once the male household head returns. Spousal income declines by about

Rs. 380 rupees at $t+1$, with losses approaching Rs. 1,000 by $t+6$. At the same time, the probability of being economically active falls by 3-6 percentage points, and the share reporting homemaking as the main occupation increases by 5-7 percentage points (Table 3.B33). These effects closely mirror those observed during separation (Table 3.B23), when spousal income rose by Rs. 650-1,000, economic activity increased by 4-8 percentage points, and homemaking declined by 6-8 percentage points. Taken together, the results indicate that spouses enter the labor market when the male household head migrates and withdraw when he returns, with household roles reverting to their earlier allocation.

With respect to other working-age household members, we largely refrain from interpretation due to statistical power. For men, most outcomes display pre-trends and the post-return sample thins, so we do not draw conclusions beyond one pattern: economic activity declines modestly after reunification, about 1.6–4.9 percentage points between $t + 2$ and $t + 6$ relative to households that remain separated, with no discernible pre-trends (Figure 3.B23 and Table 3.B34). We treat this as descriptive evidence only. For women, the post-return sample is extremely small, leaving estimates too imprecise for meaningful inference.

Turning to asset dynamics, Figure 3.9 shows that reunification is associated with a partial but selective reversal of the asset decapitalization observed during separation. The overall asset index rises steadily, with significant gains emerging from $t+2$ onward. This recovery is concentrated in durables such as computers, coolers, cars, and two-wheelers, which had previously exhibited the sharpest declines.

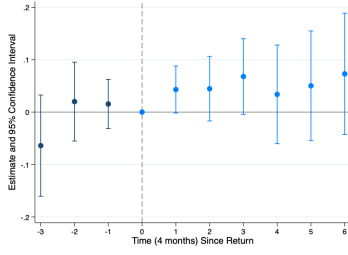
Figure 3.8: Spouse's Economic Activity after the Migrant Returns



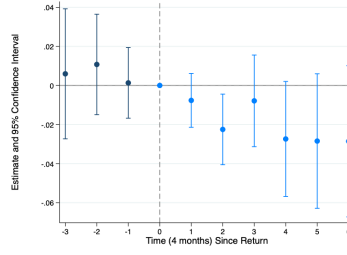
Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This figure represents spouse's economic activity after the return of the male migrant household head. Panel A presents monthly individual income (in rupees). Panel B reports whether the spouse has zero individual income. Panel C shows an indicator for whether the spouse is economically active (working or unemployed and seeking work). Panel D shows an indicator for whether the spouse is engaged in unpaid work i.e. her main occupation is “homemaker.” Panel E shows an indicator for student status as the spouse's main occupation. Table 3.B33 details the coefficients and controls shown in the figures.

Figure 3.9: Household Assets After the Migrant Returns

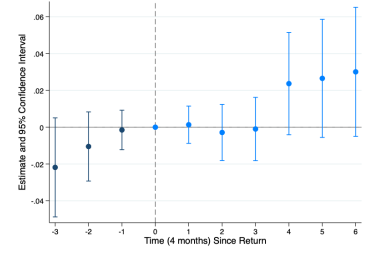
Asset Index and Appliances



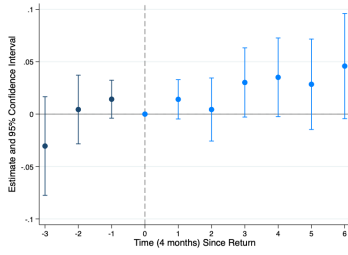
(a) Asset Index



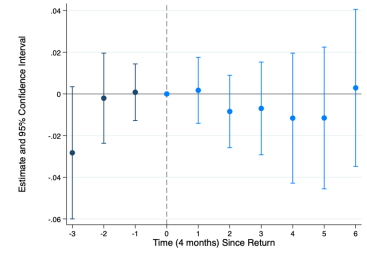
(b) Washing Machine



(c) Computers

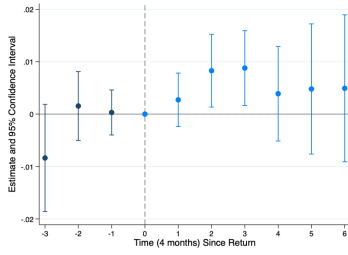


(d) Coolers

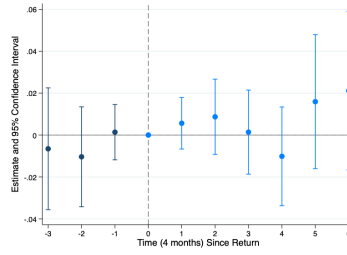


(e) Refrigerators

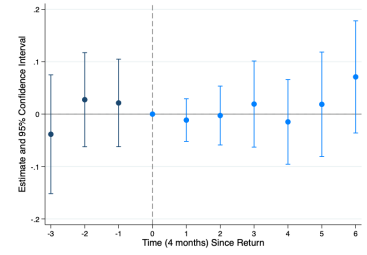
Productive Assets



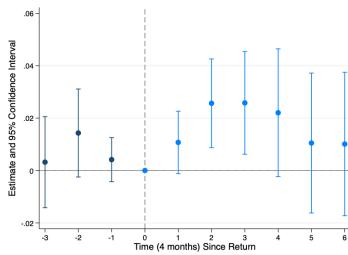
(f) Tractors



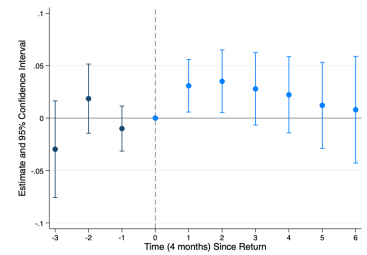
(g) Generators



(h) Cattle



(i) Cars



(j) Two Wheelers

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This figure presents asset dynamics after the return of a male migrant household head. The asset index in Panel A is a continuous measure based on PCA of binary ownership indicators. Panels B–J display binary indicators for individual asset types. Table 3.B35 and 3.B36 details the coefficients and controls shown in the figures.

These patterns are consistent with the view that some of these goods may have accompanied the migrant or been liquidated during separation and are subsequently restored upon return.

By contrast, agricultural assets do not recover. Cattle ownership remains flat, and tractors show only a weak and short-lived rebound at $t+2$ and $t+3$, dissipating thereafter, reinforcing the interpretation that reunification triggers selective replenishment rather

than broad-based asset rebuilding. In other words, while households replace or regain many consumer durables following the return of the migrant, productive capital tied to farming does not recover, pointing to a more persistent shift away from agricultural investment.

3.6 Conclusion

This paper documents how the temporary migration of male household heads reorganizes household labor supply, income composition, and asset ownership at origin. Using high-frequency panel data from India and two complementary strategies, a difference-in-differences event study and a shift-share instrumental variable design based on labor demand shocks, we trace household adjustments before, during, and after migration episodes. The interpretation of these empirical patterns is guided by a simple collective household framework that characterizes household adjustment at the onset of migration-induced separation, when remittances only partially offset the loss of male labor income at origin.

First, migration changes the composition of household income but leaves per capita income at origin largely unaffected. Wage earnings fall and household production declines, while remittances and added work by other members cushion the shortfall. On average, these offsetting shifts mean that household members at origin are no better or worse off in per capita terms. This raises an important question: if per capita income does not change, why do these people migrate? Examining heterogeneity helps resolve this puzzle partially. For poorer households, remittances replace lost wages, yielding net per capita gains, while for wealthier households the opposite holds, with remittances failing to close the gap. Since we cannot observe the migrant's own earnings at destination, these estimates reflect only the resources left behind.

To see whether conditions shift when the household head returns, we turn to reunification: wage earnings are restored, but remittances collapse and household production rises remains below pre-separation levels, again leaving per capita income broadly unchanged. Taken together, these results suggest that migration reorganizes income without raising average resources at origin, and reinforces a shift away from household production and farm-based income toward wage earnings.

Second, household labor supply responds strongly to separation. Spouses enter the labor market when the household head migrates, earning more and spending less time on homemaking. These changes largely reverse upon reunification as domestic roles resume. Other working age household members move into the labor force during separation at the expense of schooling, with suggestive evidence of a partial reversal of economic activity after return. Overall, these dynamics indicate a temporary reallocation of time, but the diversion from schooling during separation carries potential costs for human capital accumulation, especially if re-enrollment is incomplete. These labor and schooling responses are consistent with the model's theoretical predictions: female spouses increase labor market participation in response to the loss of male earnings, while young adults substitute from schooling into paid labor as a coping mechanism at the onset of separation.

Third, migration has lasting effects on household asset portfolios. Separation leads to the steady erosion of both consumer durables and productive assets, consistent with decapitalization to cope with lost income. Reunification brings only a selective recovery. The overall asset index rises, driven by gains in durables such as two-wheelers, cars, and computers, which were either liquidated or relocated during migration and are restored after return. By contrast, agricultural assets such as cattle and tractors show little to

no rebound, indicating that households do not reinvest in farm based capital once the head comes back. Migration episodes thus leave a lasting imprint on household asset composition, reinforcing a gradual shift away from agricultural investment toward non farm durables. While these asset dynamics fall outside the scope of the static framework, they complement the model by showing that some household responses to temporary migration persist well beyond the separation period.

In sum, temporary migration reorganizes household economies in ways that extend beyond the migrant's absence. While per capita income at origin remains broadly unchanged, migration reshapes the composition of earnings, reallocates household labor, and alters asset portfolios. Consistent with the conceptual framework, labor supply and schooling adjustments emerge as short-term responses to the income shock induced by separation, whereas changes in asset composition are more persistent. These uneven dynamics point to migration as a catalyst of structural change within households.

Appendix to Chapter 1

1.A Appendix

1.A.1 Data Sources and Variable Definitions

Table 1.A1 summarises the data sources used in the calibration and in the construction of the immigration flow skill shares.

Table 1.A1: Data sources

Variable	Source	Coverage
Unemployment rates (by skill, origin)	EU-LFS, UK-LFS, IPUMS-ACS	2015–2019 avg
Wage ratios (immigrant/native)	EU-SILC, IPUMS-ACS	2015–2019 avg
Skill composition (natives, immigrants)	EU-LFS, IPUMS-ACS	2015–2019 avg
Immigrant population share	EU-LFS, IPUMS-ACS	2019
GDP per capita (PPP)	World Bank WDI	2019
Effective labor tax rates (t_L , t_H)	OECD Taxing Wages	2019
Capital tax rate (t_K)	OECD Corporate Tax Statistics	2019
Capital share (α)	Penn World Table 10.0	2019
Government share of GDP	Penn World Table 10.0	2019
Public good share ($\bar{g}$ /GDP)	World Bank WDI	2019
<i>Immigration flow skill shares (Section 1.5)</i>		
EU countries (15)	EU-LFS (yearesid ≤ 4)	2019–2024
United Kingdom	UK-LFS (yearesid ≤ 4)	2019–2024
United States	IPUMS-ACS (year of entry ≤ 5 yrs)	2019–2024

Notes: Higher-skilled denotes individuals with completed tertiary education (ISCED 5 or above); lower-skilled denotes all others. Recent immigrants are defined as foreign-born individuals who arrived within the five years preceding the survey. EU-LFS and UK-LFS identify them through the harmonized duration-of-residence variable (*yearesid*, categories 0–4 or Y0–4); IPUMS-ACS uses the year-of-entry variable.

1.A.2 Welfare Decomposition: Full Country Results

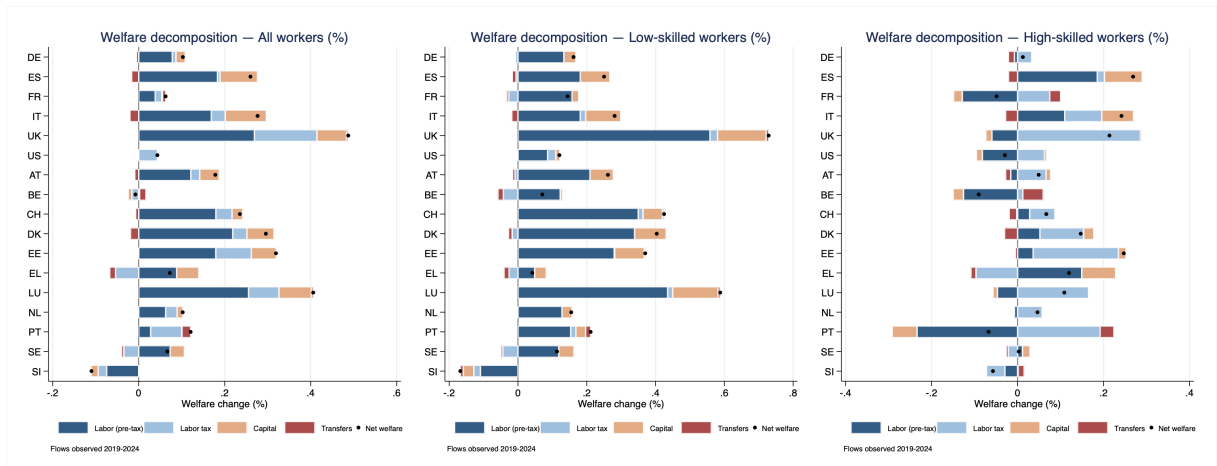
Table 1.A2 and Figure 1.A1 report the welfare decomposition for all seventeen countries in the sample, complementing Figure 1.9 in the main text.

Table 1.A2: Welfare decomposition under flows observed between 2019 and 2024

Countries	All					Lower					Higher				
	Labor pre	Labor tax	Capital	Transfers	Sum	Labor pre	Labor tax	Capital	Transfers	Sum	Labor pre	Labor tax	Capital	Transfers	Sum
Austria	0.12%	0.02%	0.05%	-0.01%	0.18%	0.21%	-0.01%	0.07%	-0.01%	0.26%	-0.02%	0.07%	0.01%	-0.01%	0.05%
Belgium	0.00%	-0.02%	-0.01%	0.01%	-0.01%	0.12%	-0.04%	0.01%	-0.02%	0.07%	-0.13%	0.01%	-0.02%	0.05%	-0.09%
Denmark	0.22%	0.03%	0.06%	-0.02%	0.30%	0.34%	-0.02%	0.09%	-0.01%	0.40%	0.05%	0.10%	0.02%	-0.03%	0.15%
Estonia	0.18%	0.08%	0.06%	0.00%	0.32%	0.28%	0.00%	0.09%	0.00%	0.37%	0.04%	0.20%	0.02%	-0.01%	0.25%
France	0.04%	0.02%	0.00%	0.01%	0.06%	0.16%	-0.03%	0.02%	-0.01%	0.14%	-0.13%	0.07%	-0.02%	0.03%	-0.05%
Germany	0.08%	0.01%	0.02%	-0.01%	0.10%	0.13%	-0.01%	0.04%	0.00%	0.16%	-0.01%	0.03%	0.00%	-0.01%	0.01%
Greece	0.09%	-0.05%	0.05%	-0.01%	0.07%	0.05%	-0.03%	0.03%	-0.01%	0.04%	0.15%	-0.10%	0.08%	-0.01%	0.12%
Italy	0.17%	0.03%	0.10%	-0.02%	0.27%	0.19%	0.02%	0.10%	-0.02%	0.29%	0.11%	0.09%	0.07%	-0.03%	0.24%
Luxembourg	0.26%	0.07%	0.08%	0.00%	0.41%	0.44%	0.01%	0.13%	0.01%	0.59%	-0.05%	0.17%	-0.02%	0.00%	0.10%
Netherlands	0.06%	0.03%	0.01%	0.00%	0.10%	0.13%	0.00%	0.03%	0.00%	0.15%	-0.01%	0.06%	0.00%	0.00%	0.05%
Portugal	0.03%	0.07%	0.00%	0.02%	0.12%	0.15%	0.01%	0.03%	0.01%	0.21%	-0.23%	0.19%	-0.06%	0.03%	-0.07%
Slovenia	-0.07%	-0.02%	-0.02%	0.00%	-0.11%	-0.11%	0.00%	-0.03%	-0.01%	-0.15%	-0.03%	-0.04%	0.00%	0.01%	-0.06%
Spain	0.18%	0.01%	0.09%	-0.02%	0.26%	0.18%	-0.01%	0.09%	-0.01%	0.25%	0.19%	0.02%	0.09%	-0.02%	0.27%
Sweden	0.07%	-0.03%	0.03%	-0.01%	0.07%	0.12%	-0.04%	0.04%	-0.01%	0.11%	0.01%	-0.02%	0.02%	-0.01%	0.00%
Switzerland	0.18%	0.04%	0.03%	-0.01%	0.24%	0.35%	0.01%	0.06%	0.00%	0.42%	0.03%	0.06%	0.00%	-0.02%	0.07%
United Kingdom	0.27%	0.15%	0.07%	0.00%	0.49%	0.56%	0.02%	0.14%	0.01%	0.73%	-0.06%	0.29%	-0.01%	0.00%	0.21%
United States	0.00%	0.04%	0.00%	0.00%	0.04%	0.09%	0.02%	0.01%	0.00%	0.12%	-0.08%	0.06%	-0.01%	0.00%	-0.03%
Mean	0.11%	0.03%	0.04%	0.00%	0.17%	0.20%	-0.01%	0.06%	0.00%	0.24%	-0.01%	0.07%	0.01%	0.00%	0.07%

Notes: Welfare effects are expressed as percentage changes in steady-state consumption equivalents following a one percentage point increase in immigration using the skill composition of 2019–2024 flows. Each entry reports the contribution of a single channel to the total welfare change (Sum). See Section 1.5 for discussion.

Figure 1.A1: Welfare decomposition by channel — All countries



Notes: Each panel reports the welfare decomposition for native workers following a one percentage point increase in immigration, using skill shares observed in 2019–2024 immigration flows. Welfare effects are expressed as percentage changes in steady-state consumption equivalents and decomposed into four channels: labor income (pre-tax), labor tax, capital income, and transfers. Positive components are stacked rightward from zero; negative components are stacked leftward. The black dot indicates the net welfare effect (sum of all components). Panels correspond to all natives, low-skilled natives, and high-skilled native.

Appendix to Chapter 2

2.A Appendix

2.A.1 Derivation of Migration Choice Probabilities

This appendix derives the closed-form expression for the migration choice probabilities used in the main text.

When considering the logit choice model, destination country j is selected by family f based on a comparison of utility across all feasible locations. Let j denote the chosen destination, and let d index alternative locations, which may include both the current country of residence and other potential destinations.

The probability that family f chooses country j is given by:

$$P_{f,j} = \Pr (C_{f,j} + v_{f,j} > C_{f,d} + v_{f,d}, \forall d \neq j), \quad (2.A1)$$

where $C_{f,j}$ denotes the deterministic component of utility in country j , and $v_{f,j}$ is an idiosyncratic preference shock.

Assume that $v_{f,j}$ are independently and identically distributed according to a Type I extreme value distribution with cumulative distribution function:

$$F(v) = \exp(-e^{-v}). \quad (2.A2)$$

Conditional on a realization of $v_{f,j}$, the probability that country j is preferred to all other destinations is:

$$P_{f,j} \mid v_{f,j} = \prod_{d \neq j} \Pr(v_{f,d} < v_{f,j} + C_{f,j} - C_{f,d}). \quad (2.A3)$$

Using the cumulative distribution function of $v_{f,d}$, this expression can be written as:

$$P_{f,j} \mid v_{f,j} = \prod_{d \neq j} \exp\left(-e^{-(v_{f,j} + C_{f,j} - C_{f,d})}\right). \quad (2.A4)$$

Since $v_{f,j}$ is unobserved, the unconditional choice probability integrates over its density. The density of the Type I extreme value distribution is:

$$f(v) = e^{-v} \exp(-e^{-v}). \quad (2.A5)$$

Hence, the unconditional choice probability is:

$$P_{f,j} = \int_{-\infty}^{\infty} \left[\prod_{d \neq j} \exp \left(-e^{-(v+C_{f,j}-C_{f,d})} \right) \right] e^{-v} \exp \left(-e^{-v} \right) dv. \quad (2.A6)$$

Let $s = v$. Then:

$$\begin{aligned} P_{f,j} &= \int_{-\infty}^{\infty} \exp \left(- \sum_{d \neq j} e^{-(s+C_{f,j}-C_{f,d})} \right) e^{-s} \exp \left(-e^{-s} \right) ds \\ &= \int_{-\infty}^{\infty} \exp \left(-e^{-s} \sum_d e^{-(C_{f,j}-C_{f,d})} \right) e^{-s} ds. \end{aligned} \quad (2.A7)$$

Define the change of variables $t = e^{-s}$, so that $dt = -e^{-s} ds = -t ds$.

As $s \rightarrow \infty$, $t \rightarrow 0$, and as $s \rightarrow -\infty$, $t \rightarrow \infty$. The integral becomes:

$$\begin{aligned} P_{f,j} &= \int_{\infty}^0 \exp \left(-t \sum_d e^{-(C_{f,j}-C_{f,d})} \right) (-dt) \\ &= \int_0^{\infty} \exp \left(-t \sum_d e^{-(C_{f,j}-C_{f,d})} \right) dt. \end{aligned} \quad (2.A8)$$

Evaluating the integral yields:

$$\begin{aligned} P_{f,j} &= \frac{\exp \left(-t \sum_d e^{-(C_{f,j}-C_{f,d})} \right)}{\sum_d e^{-(C_{f,j}-C_{f,d})}} \Bigg|_0^{\infty} \\ &= \frac{1}{\sum_d e^{-(C_{f,j}-C_{f,d})}} = \frac{e^{C_{f,j}}}{\sum_d e^{C_{f,d}}}. \end{aligned} \quad (2.A9)$$

This expression corresponds to the standard multinomial logit choice probability. It represents the share of families of a given skill type that choose destination j relative to all alternative locations d . These choice probabilities govern the endogenous sorting of households across countries and are central to understanding how migration incentives translate into observed patterns of skill composition and fiscal impact across destinations.

Appendix to Chapter 3

3.A Appendix

3.A.1 Theoretical Predictions

Proposition 1. *Increase in Female Labor Supply*

Proof: From the female optimal labor supply as showed in Equation (3.13) we derive the partial derivative in order to check the negative sign.

$$\frac{\partial l_f^*}{\partial w_m} = \frac{-(1 - \alpha_f)\rho \cdot \alpha_y}{w_f [\alpha_f + (1 - \alpha_f)\rho\alpha_y]} < 0 \quad (3.A1)$$

A decline in Y reduces c_f , raising the marginal utility of consumption. To restore utility balance between consumption and home production, the female increases her labor supply, implying an increase in optimal labor l_f^* and a decrease in home production h_f , given the time constraint. ■

Proposition 2. *Increase in Young Adult Labor Supply*

Proof: When the male household head migrates, household income falls. Even though remittances R are received, they only partially offset the lost labor income. As a result, youth consumption c_y declines, increasing the marginal utility of consumption due to the logarithmic form of preferences. From the youth optimal labor supply function in Equation (3.14) we take the partial derivative with respect to w_m to check the direction of the sign:

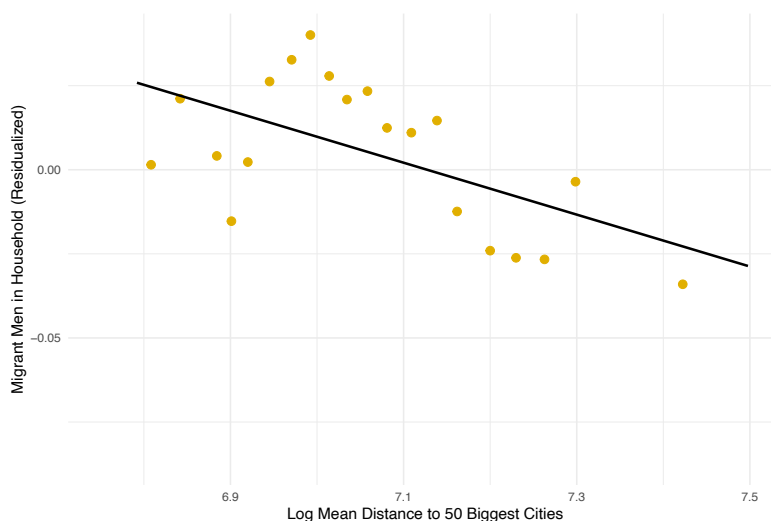
$$\frac{\partial l_y^*}{\partial w_m} = \frac{-(1 - \alpha_y)}{\alpha_f + (1 - \alpha_f)\rho\alpha_y} < 0 \quad (3.A2)$$

As household income Y decreases due to $w_m < R$, there is an increase in optimal labor supply l_y^* . Thus, following male migration, the youth increases time spent in paid labor to help sustain household consumption.

Proof of Proposition 3 follows from Proposition 2, given the time endowment, i.e., $s_y = 1 - l_y$. ■

3.A.2 District remoteness and migration

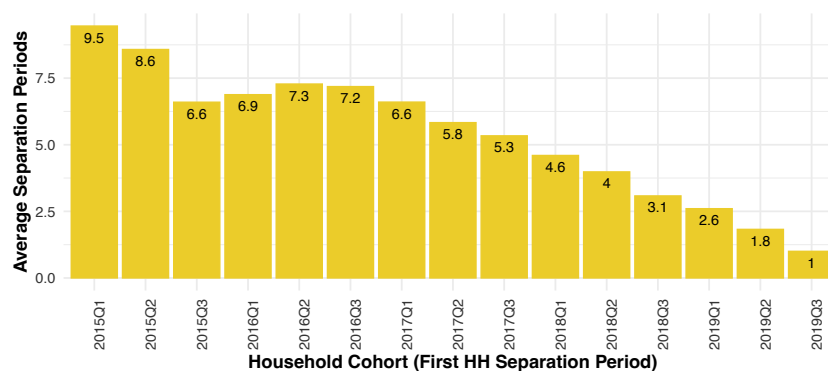
Figure 3.A1: Binscatter Plot of Working Age Male Migrants and Distance to Largest Cities



Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014 to 2019. Y-axis is number of working age male migrants, residualized after taking quadrimester fixed effects. X-axis is log of mean distance from each district to the 50 biggest districts by population. The black line is the best linear fit, constructed from an OLS regression of y-residuals on x.

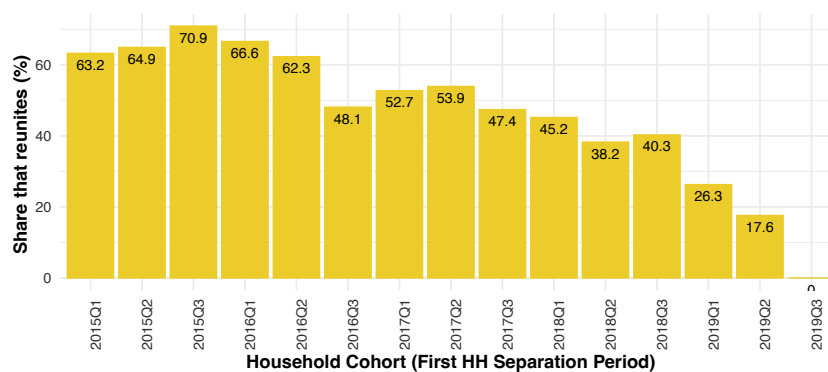
3.A.3 Household separation by cohort

Figure 3.A2: Average periods of separation by cohort



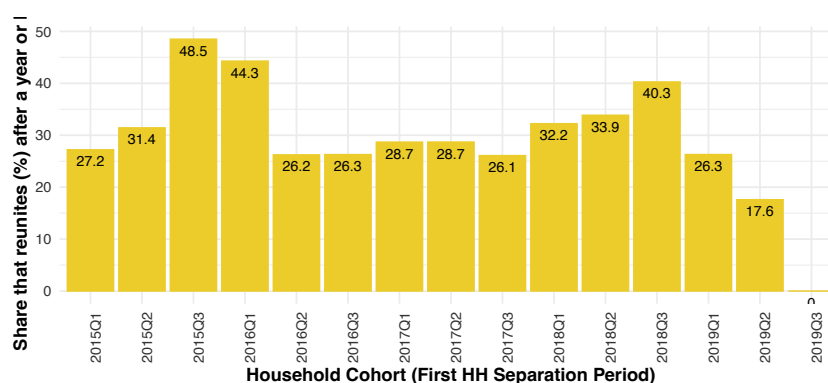
Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014 to 2019. Y-axis is average periods of separation per household. X-axis is the household cohort, or first period of separation. The sample corresponds to our main analysis: i) is together at baseline (2014), the male household head migrates unaccompanied by a female household head, iii) the household is present between 2014 and 2019.

Figure 3.A3: Share of household that reunites by cohort



Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014 to 2019. Y-axis is the share of households that reunited after being separated by the migration of the male household head. X-axis is the household cohort, or first period of separation. The sample corresponds to our main analysis: i) is together at baseline (2014), the male household head migrates unaccompanied by a female household head, iii) the household is present between 2014 and 2019.

Figure 3.A4: Share of household that reunites after a year or less by cohort



Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014 to 2019. Y-axis is the share of households that reunited after being separated by the migration of the male household head for a year or less. X-axis is the household cohort, or first period of separation. The sample corresponds to our main analysis: i) is together at baseline (2014), the male household head migrates unaccompanied by a female household head, iii) the household is present between 2014 and 2019.

3.A.4 Summary Statistics

Table 3.A1: Household Migration Patterns

	Number of Households
Total Households	4703
Total 4-months periods	18.0
Mean periods with separation	5.0
Households switch 0 to 1 (not separated to separated)	4703
Households switch 1 to 0 (reunification)	2042
Households with baseline 0 for at least 4 periods	4435
... and separated for 3 consecutive periods	2710
... and separated for 6 consecutive periods	1452
Household separated for a year or less and return	1320

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014 to 2019. The sample corresponds to the households whose male married working-age (18–60) member or whose member listed as the head or spouse in the household roster, migrated unaccompanied by a female spouse.

Table 3.A2: Characteristics of male household head migrant

Covariate	(1) Mean
Unique HHs	4703
Age	35.84 (10.52)
Worked before migrating	0.75 (0.44)
Income before migrating	10247.87 (8182.59)
Occupation: Business/Entrepreneur	0.16 (0.37)
Occupation: Salaried worker	0.26 (0.44)
Occupation: Farmers	0.11 (0.31)
Occupation: Small traders & informal daily earners	0.30 (0.46)
Occupation: Student	0.06 (0.24)
Occupation: Retired	0.02 (0.12)
Occupation: Home Maker	0.09 (0.29)
Has high school education	0.54 (0.50)
Has higher education	0.22 (0.42)

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014 to 2019. The sample corresponds to male married working-age (18–60) members or (those listed as the male head or spouse in the household roster) that migrated unaccompanied by a female spouse.

Table 3.A3: Characteristics of households with male migrant separation

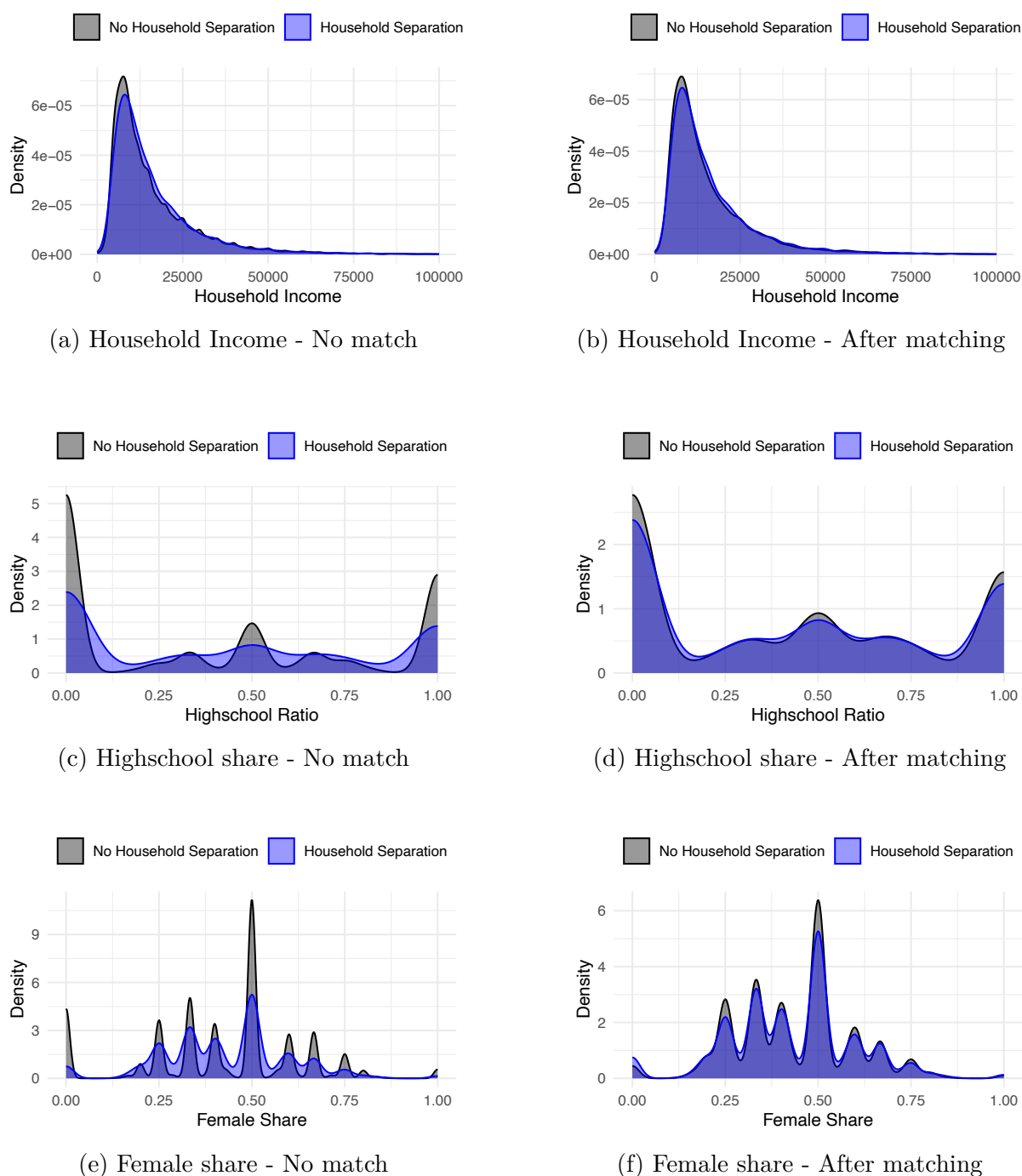
	(1) No household separation	(2) Male household separation	(3) Difference
Unique households	213594	4703	
Household income	13266 (12301)	13022 (11232)	-244.22
Household size	4.35 (1.57)	4.54 (1.53)	0.19***
Share of females	0.43 (0.20)	0.43 (0.18)	0.00
Share of over 60 and under 18	0.40 (0.24)	0.39 (0.24)	-0.00
No working age members with complete high school	0.53 (0.50)	0.53 (0.50)	-0.00
All working age member with complete high school	0.16 (0.36)	0.13 (0.34)	-0.02***
Area: Urban very large	0.12 (0.32)	0.05 (0.22)	-0.06***
Area: Urban large	0.04 (0.20)	0.03 (0.17)	-0.01***
Area: Urban median	0.04 (0.20)	0.03 (0.17)	-0.01***
Area: Urban small	0.11 (0.31)	0.09 (0.29)	-0.02***
Area: Rural	0.69 (0.46)	0.80 (0.40)	0.10***
Main occupation: Business/Entrepreneur	0.14 (0.35)	0.11 (0.32)	-0.03***
Main occupation: Salaried worker	0.14 (0.35)	0.17 (0.37)	0.02**
Main occupation: Farmers	0.23 (0.42)	0.23 (0.42)	0.01
Main occupation: Small traders & informal daily earners	0.37 (0.48)	0.37 (0.48)	-0.00
Main occupation: Retired/student/home maker	0.12 (0.33)	0.12 (0.32)	-0.00
Occupation: Missing data	0.36 (0.48)	0.00 (0.07)	-0.35***
Caste: Upper	0.16 (0.36)	0.22 (0.41)	0.06***
Caste: Intermediate	0.08 (0.27)	0.06 (0.24)	-0.02***
Religion: Hindu	0.67 (0.47)	0.82 (0.39)	0.15***
Religion: Muslim	0.07 (0.26)	0.10 (0.30)	0.03***
Religion: Sikh	0.02 (0.14)	0.01 (0.12)	-0.01***

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014 to 2019. Column (1) reports baseline characteristics—defined as the first observed wave—for households in which no migration by the household head occurs. We define the household head as a married, working-age (18–65) member listed as the head or spouse in the household roster, regardless of gender. Column (2) reports baseline characteristics for households treated for our analysis, which i) experienced a separation event due to the migration of the male household head, ii) the household is not separated at baseline (2014), and (iii) the household is observed in all waves between 2014 and 2019. Column (3) presents the difference in means between the two groups. All estimates are weighted using survey weights to ensure national representativeness. *p<0.1; **p<0.05; ***p<0.0

3.A.5 Matching method

To improve the comparability between treated and control households, we implement a nearest-neighbor matching procedure. Treated households are those that experience separation due to male household head migration, and control households are those that remain intact throughout the panel period. We match each treated household to two control households (1:2 ratio) using nearest-neighbor matching with a caliper of 0.2 on a probit estimation to predict propensity scores. The matching is performed by district and the propensity score is estimated using a rich set of baseline household characteristics. These include total income, household size, female share, and a vulnerability index, as well as educational attainment (no high school, some high school, and full high school), strata dummies (very large urban, large urban, medium urban, small urban, and rural), and baseline occupations (business, salaried work, farming, small traders, other). We also include an indicator for missing data. The resulting matched control group closely resembles the treatment group on observed characteristics, as shown in Table 3.A4. The following Table 3.A5 shows the fit of distribution of baseline continuous variables between the control and the treatment.

Figure 3.A5: Distribution of baseline continuous variables, before and after matching



Notes: Data are from the Consumer Pyramids Household Survey (CPHS), 2014–2019. Kernel densities of baseline covariates for treated households (separation) and controls, before and after matching. Matching is within district using nearest neighbor (1:2) with a 0.2 caliper on the propensity score estimated from baseline income, household size, female share, education, strata, baseline occupations, a vulnerability index, and a missing-data flag. Panels show household income, share with high school, and female share.

Table 3.A4: Balance Table: Match Control

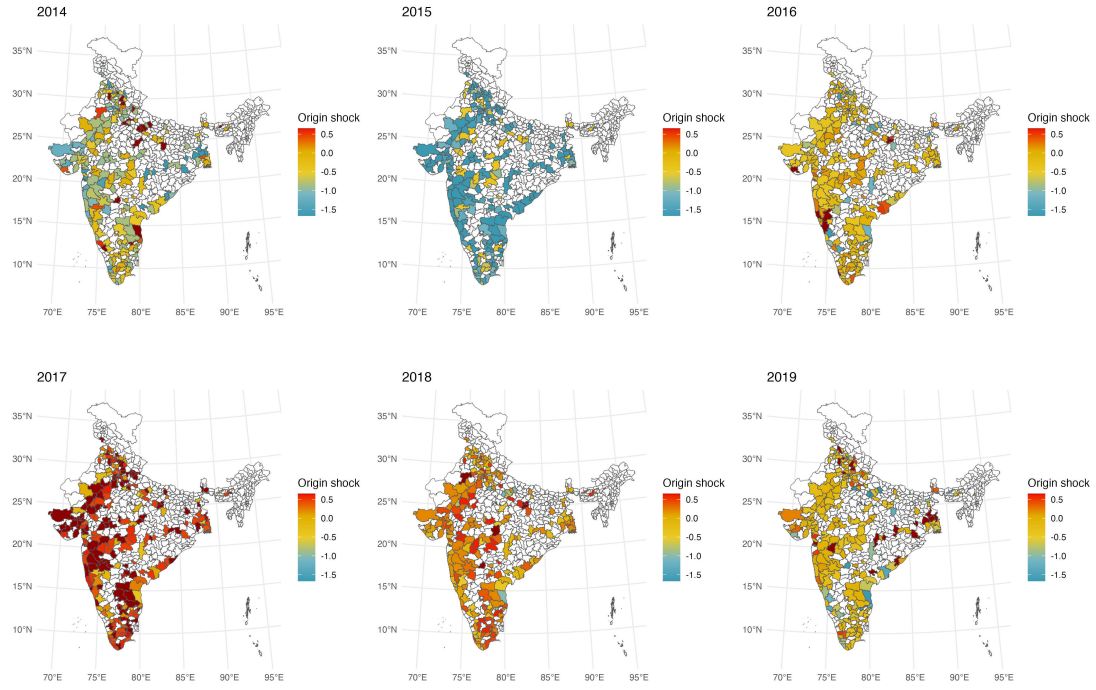
Covariate	(1) Matched Control	(2) Treat	(3) Difference
Unique HHs	9134	4610	
Matching variables:			
Household income	12671.75 (10835.95)	12954.53 (11085.13)	282.78
Household size	4.51 (1.53)	4.54 (1.51)	0.04
Share of females	0.43 (0.16)	0.43 (0.17)	0.00
Share of over 60 and under 18	0.39 (0.23)	0.39 (0.24)	0.00
No working age members with complete highschool	0.52 (0.50)	0.53 (0.50)	0.01
All working age member with complete highschool	0.13 (0.34)	0.13 (0.34)	0.01
Area: Urban very large	0.05 (0.23)	0.05 (0.22)	-0.00
Area: Urban large	0.03 (0.17)	0.03 (0.17)	0.00
Area: Urban median	0.03 (0.18)	0.03 (0.17)	-0.00
Area: Urban small	0.10 (0.30)	0.09 (0.29)	-0.01
Area: Rural	0.78 (0.41)	0.79 (0.41)	0.01
Main occupation: Business/Entrepreneur	0.12 (0.32)	0.11 (0.32)	-0.00
Main occupation: Salaried worker	0.14 (0.35)	0.17 (0.37)	0.02*
Main occupation: Farmers	0.24 (0.43)	0.23 (0.42)	-0.00
Main occupation: Small traders	0.39 (0.49)	0.37 (0.48)	-0.02
Main occupation: Retired/student/home maker	0.11 (0.31)	0.11 (0.32)	0.00
Occupation: Missing data	0.01 (0.08)	0.00 (0.07)	-0.00
Other variables:			
Caste: Upper	0.20 (0.40)	0.22 (0.41)	0.01
Caste: Intermediate	0.07 (0.25)	0.06 (0.24)	-0.00
Religion: Hindu	0.83 (0.38)	0.82 (0.39)	-0.01
Religion: Muslim	0.08 (0.28)	0.10 (0.30)	0.02
Religion: Sikh	0.02 (0.12)	0.01 (0.12)	-0.00
Had another migrant at baseline	0.15 (0.35)	0.14 (0.35)	-0.00

Notes: Data are from the CPHS, 2014–2019. Treated households are those that later experience separation due to migration of the male household head; matched controls are selected within district using nearest–neighbor matching (1:2) with a 0.2 caliper on the propensity score estimated from baseline covariates (see Section 3.A.5). All covariates are measured in the pre-separation (baseline) wave. Columns report means with standard deviations in parentheses for matched controls (1) and treated (2); Column (3) is the difference in means (Treated minus Matched Control). Estimates use survey weights. Stars indicate a test of equality of means: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

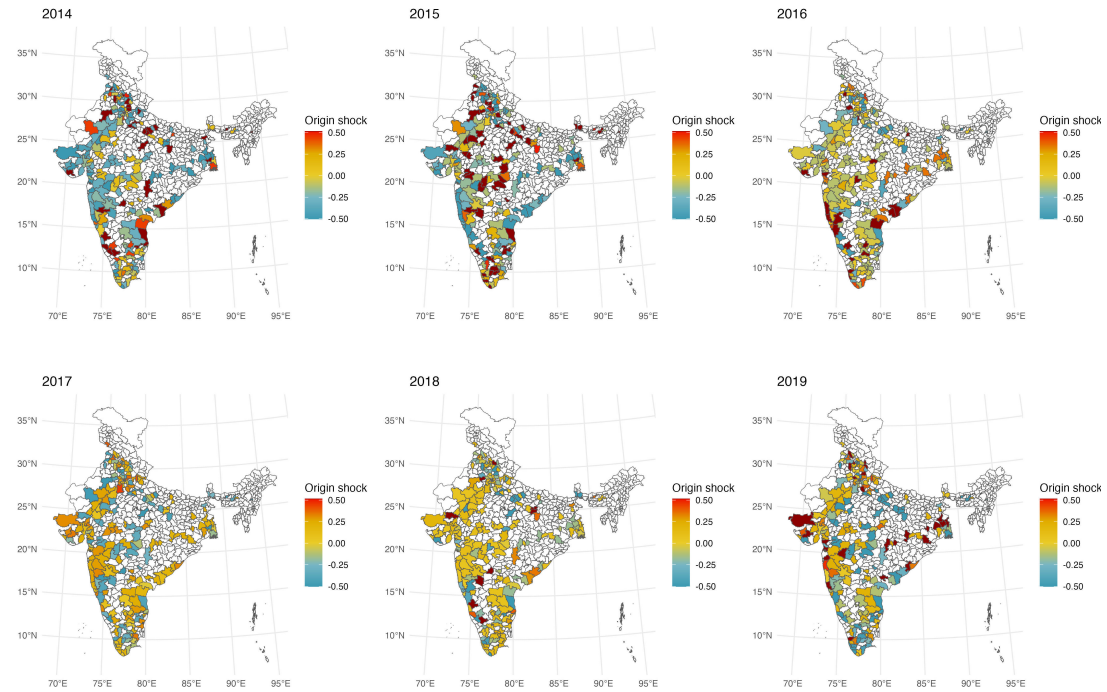
3.A.6 Employment pull variation

We visualize the geographic variation of the labor demand shocks used in our instrumental variable strategy. Figure 3.A6 plots the destination-level employment pull component (x_{dt}), while Figure 3.A7 displays the corresponding origin-level exposure s_{ot} , constructed as a leave-one-out inverse-distance weighted sum: $s_{ot} = \sum_{d \in \Theta \setminus o} \frac{x_{dt}}{\tau_{od}}$. These maps show substantial spatial and temporal variation in exposure to labor demand shocks. This variation becomes even more pronounced once we account for district and year fixed effects in Panel B of both figures. These controls are part of our 2SLS, which reveals the variation used in our empirical analysis.

Figure 3.A6: Employment pull at destination district x_{dt}



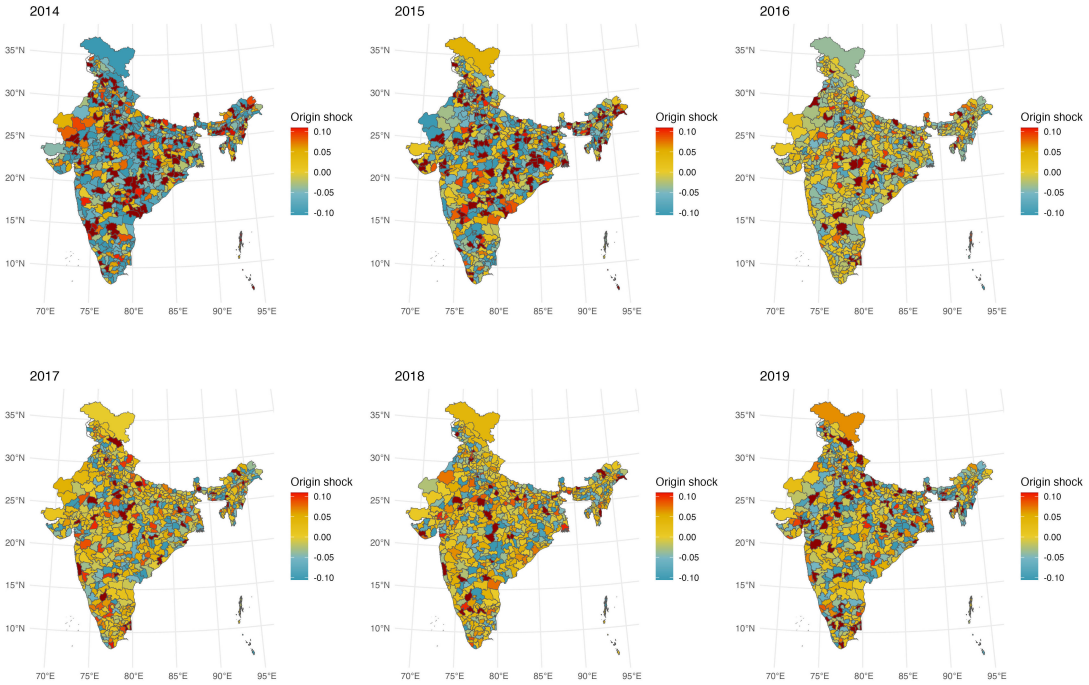
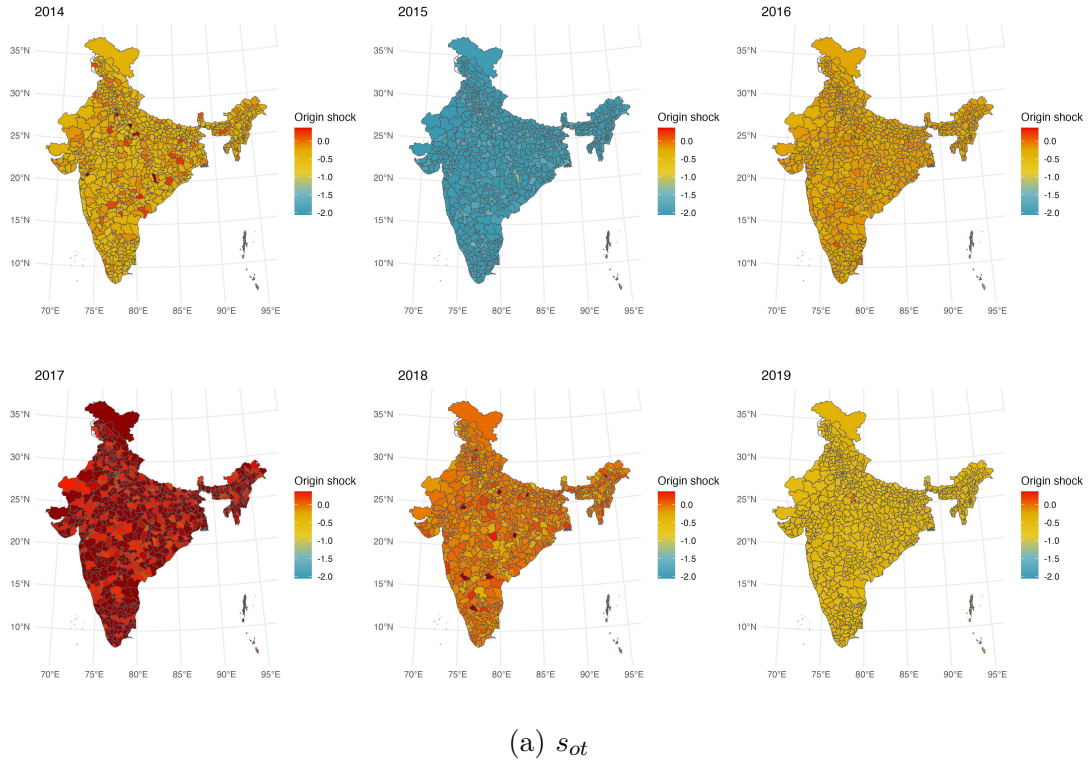
(a) x_{dt}



(b) x_{dt} residualized fixed effects on time and district

Notes: Data are from the Consumer Pyramids Household Survey (CPHS), 2014–2019. Maps show the destination–district employment pull shock, x_{dt} , for 2014–2019. Panel (a) plots raw values; Panel (b) plots values residualized on district and year fixed effects to align with the 2SLS specification. Values are standardized within year.

Figure 3.A7: Leave-on-out employment pull at origin s_{ot}



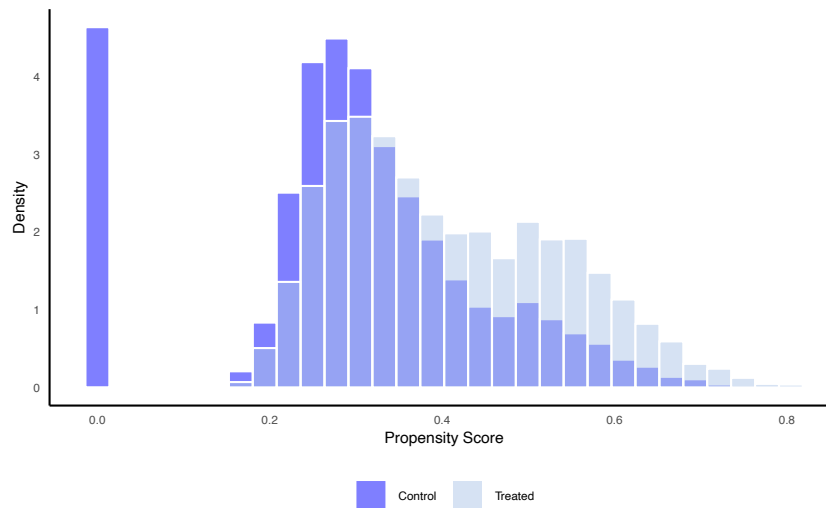
Notes: Data are from the Consumer Pyramids Household Survey (CPHS), 2014–2019. Maps show the origin–district exposure to destination shocks, $s_{ot} = \sum_{d \neq o} x_{dt} / \tau_{od}$, computed as a leave-one-out inverse-distance weighted sum. Panel (a) plots raw exposure; Panel (b) plots exposure residualized on origin-district and year fixed effects. Values are standardized within year.

3.A.7 Propensity for household head migration

We estimate λ_{io} , the specific propensity of the household to experience separation due to migration of the heads of the male household, which serves as the share component in our shift-share instrument. To estimate this parameter, we run household-level logistic regressions that predict treatment status (migration-induced separation) as a function of baseline characteristics. The dependent variable is an indicator for whether the household experiences migration-induced separation at any point during the panel (2014–2019). The covariates include household income, size, female share, age composition, urban-rural strata, and baseline labor market variables like household occupation types. We also include education levels, and previous migration history of a household member. We run and predict these propensities by region, to allow for regional heterogeneity. The resulting fitted values from these regressions represent the predicted probability that the household experiences separation, or the propensity to separation.

As shown in Figure 3.A8, the estimated distribution of household propensities of separation (λ_{io}) overlaps between the treatment and the matched control groups, with treated household having higher predicted probabilities of separation, indicating sufficient common support for identification.

Figure 3.A8: Estimated propensity λ_{io} by treatment status



Notes: Data are from the Consumer Pyramids Household Survey (CPHS), 2014–2019. Histogram of fitted household propensities to separate, λ_{io} , from baseline logistic models (estimated by region). Dark bars show treated households; light bars show matched controls.

3.A.8 First stage

The shift-share instrument strongly predicts household separation due to the migration of the male household head, as shown in Table 3.A5. The dependent variable is 1 if the household is separated for at least one period during the year. The weighted price shocks s_{ot} and x_{ot} have been standardized. On average, each year, 13% of the households experience separation. The first coefficient to z_{iot} implies that one standard deviation increase in the leave-one-out export price shock increases the likelihood to separate by approximately 10.5 percentage points if the propensity to separate is 1 ($\lambda_{io} = 1$). The F-statistics is 116, well above the rule-of-thumb of 10.

Table 3.A5: First Stage: Distance-Weighted Export Shocks and Household Separation

	(1)	(2)	(3)
Mig_{iot}			
$z_{iot} = s_{ot} \times \lambda_{io}$	0.105*** (0.00951)	0.105*** (0.00967)	0.105*** (0.00971)
s_{ot}		0.00365 (0.0122)	0.00456 (0.0123)
x_{ot}			0.00306 (0.00282)
KP (F-stat)	122.7	117.7	116.4
Within R2	0.00462	0.00461	0.00463
Outcome Mean	0.130	0.130	0.130
Observations	76936	76936	76936

Notes: Data are from the Consumer Pyramids Household Survey (CPHS), 2014–2019. The dependent variable is an indicator for household separation in year t , Mig_{iot} . The instrument is $z_{iot} = s_{ot} \times \lambda_{io}$, where s_{ot} is the leave-one-out, distance-weighted export price shock for the origin district and λ_{io} is the household’s baseline propensity to separate. x_{ot} is the un-interacted origin shock. All regressions include household and year fixed effects. Standard errors (in parentheses) are clustered at the origin-district level. “KP (F-stat)” is the Kleibergen–Paap rk F-statistic for the excluded instrument. “Outcome mean” is the annual share of households that separate. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3.A.9 Compliers

To describe the characteristics of compliers, never-takers, and always-takers, we follow the method proposed in [Hangartner et al. \(2021\)](#), which extends the Local Average Treatment Effect (LATE) framework of [Angrist et al. \(1996\)](#). Under standard IV assumptions, (i) a binary instrument, (ii) a binary treatment, (iii) monotonicity (no defiers), (iv) exclusion (the instrument affects the outcome only through treatment), and (v) independence (the instrument is as good as randomly assigned), the sample is partitioned into three latent types: always-takers, who receive treatment regardless of the instrument; never-takers, who never receive treatment; and compliers, whose treatment status responds to the instrument. For each covariate, the method nonparametrically recovers group-specific means and standard errors by leveraging variation in the instrument and treatment.

In our setting, the instrument is a continuous variable capturing predicted exposure (z_{iot}). To apply this method, we discretize the instrument by creating a binary version that equals one if the residualized instrument is above its sample median. The residualization step accounts for our full set of controls: time-invariant spatial characteristics (s_{ot}), destination employment pull (x_{dt}), as well as household and year fixed effects. This ensures that the binary instrument used for compliance classification is orthogonal to the included covariates and reflects quasi-experimental variation in treatment assignment.

Table 3.A6: Descriptive Statistics by Compliance Type

Covariate	Complier	Never Taker	Always Taker
Mortality after separation	-0.00 (0.02)	0.20 (0.00)	0.19 (0.01)
Household income	15216 (820)	19656 (146)	19721 (277)
Income per Capita	4667 (217)	4890 (37)	4642 (72)
Has newborn	0.01 (0.01)	0.03 (0.00)	0.04 (0.00)
Household size	4.31 (0.08)	4.53 (0.01)	4.53 (0.02)
Share of females	0.46 (0.01)	0.43 (0.00)	0.43 (0.00)
Share of over 60 and under 18	0.38 (0.01)	0.35 (0.00)	0.35 (0.00)
No working age members with complete highschool	0.36 (0.02)	0.40 (0.00)	0.40 (0.01)
All working age member with complete highschool	0.22 (0.02)	0.23 (0.00)	0.24 (0.01)
Area: Urban very large	0.07 (0.01)	0.11 (0.00)	0.11 (0.01)
Area: Urban large	0.07 (0.02)	0.14 (0.00)	0.11 (0.01)
Area: Urban median	0.22 (0.02)	0.19 (0.00)	0.19 (0.01)
Area: Urban small	0.36 (0.02)	0.21 (0.00)	0.22 (0.01)
Area: Rural	0.28 (0.02)	0.35 (0.00)	0.37 (0.01)
Main occupation: Business/Entrepreneur	0.21 (0.02)	0.19 (0.00)	0.19 (0.01)
Main occupation: Salaried worker	0.13 (0.02)	0.20 (0.00)	0.18 (0.01)
Main occupation: Farmers	0.14 (0.02)	0.11 (0.00)	0.13 (0.01)
Main occupation: Small traders	0.37 (0.02)	0.33 (0.00)	0.33 (0.01)
Main occupation: Retired/student/home maker	0.15 (0.02)	0.18 (0.00)	0.17 (0.01)

Notes: Data are from the Consumer Pyramids Household Survey (CPHS), 2014–2019. The table reports covariate means by compliance type in column (1) for Compliers, column (2) for Never-takers and column (3) for Always-takers, estimated following [Hangartner et al. \(2021\)](#) within the LATE framework of [Angrist et al. \(1996\)](#).

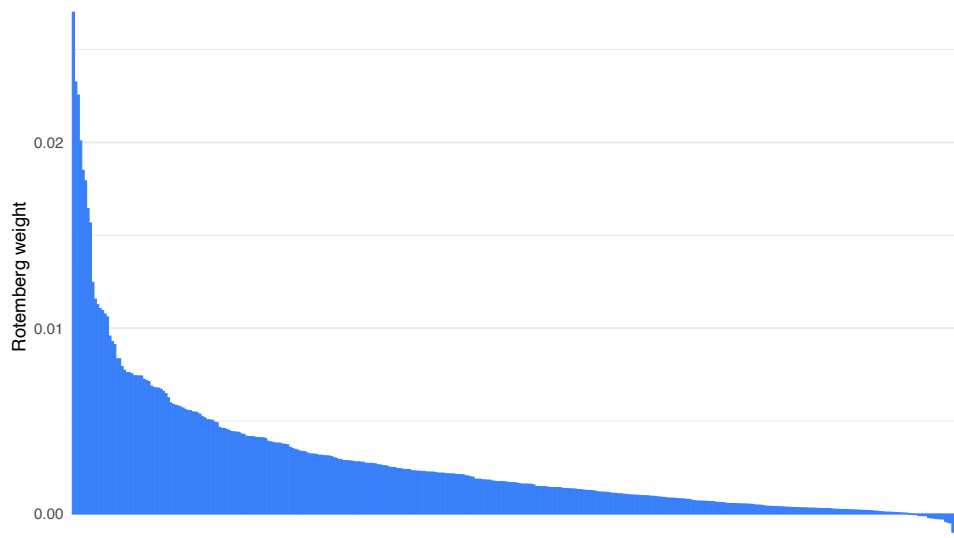
3.A.10 Rotemberg weights

To assess the contribution of each origin location to our instrumented treatment effect, we compute Rotemberg weights, adapted to shift-share designs by [Goldsmith-Pinkham, Sorkin, and Swift \(Goldsmith-Pinkham et al.\)](#). Intuitively, the Rotemberg weights reflect the implicit influence that each location-specific shock has on the overall IV estimate. A higher weight implies that the corresponding shock contributes more to the identification of the causal effect. We implement this in several steps:

1. Recover the fitted values of the endogenous variable from the first stage. Using the 2SLS regression where household separation is instrumented by the shift-share term ($z_{iot} = \lambda_{io} \cdot s_{ot}$), we obtain the fitted values $\hat{Mig}_{iot}$ from the first stage.
2. Compute the product of the fitted treatment and the shock s_{ot} . The product of these two components gives the contribution of each location's shock to the overall IV estimate.
3. Aggregate these contributions by geographic unit (state or district). We sum the contributions across observations to get the total contribution by location.
4. Normalize the contributions to obtain the Rotemberg weights. Each location's contribution is divided by the total to yield a weight that sums to one.
5. The resulting weights quantify which locations drive identification in the instrument to infer the geographic structure of the LATE.

Figure 3.A9 shows that weights are broadly dispersed across districts with a long, thin right tail. No single district dominates the instrument: the largest district receives 2.7% of the total weight, and the top fifteen districts together account for about 24% (Table 3.A7). The remaining three quarters of the identifying variation is spread across many districts. Overall, the distribution does not suggest undue concentration of identifying variation.

Figure 3.A9: Distribution of Rotemberg weights



Notes: Data are from the Consumer Pyramids Household Survey (CPHS), 2014–2019. Rotemberg weights by origin district. Each bar shows a district's contribution to identification in the shift-share IV; weights are normalized to sum to one.

Table 3.A7: Top 15 Rottemberg Weights per District

State	District	Rotemberg Weight
Bihar	Gopalganj	0.027
Uttar Pradesh	Basti	0.023
Uttar Pradesh	Kanpur Nagar	0.023
Bihar	Purba Champaran	0.020
Andhra Pradesh	Sri Potti Sriramulu Nellore	0.018
Bihar	Saran	0.018
Uttar Pradesh	Faizabad	0.016
Uttar Pradesh	Sultanpur	0.016
Uttar Pradesh	Allahabad	0.012
Rajasthan	Alwar	0.012
Uttar Pradesh	Meerut	0.011
West Bengal	Haora	0.011
Uttar Pradesh	Bahraich	0.011
Bihar	Patna	0.011
Uttar Pradesh	Jaunpur	0.011

Notes: Data are from the Consumer Pyramids Household Survey (CPHS), 2014–2019. The table lists the fifteen districts with the largest Rotemberg weights (district contributions to identification in the shift–share IV). Weights are unitless and sum to one.

3.A.11 Balance on treatment intensity

We examine whether the intensity of treatment varies systematically with households' underlying propensity to migrate. Table 3.A8 reports regressions of the export pull shock at origin district, s_{ot} , on the household-level migration propensity, λ_{io} , along with a set of progressively richer controls. Columns (1)–(3) sequentially add controls including household characteristics, year fixed effects, and district fixed effects. Column (4), which includes both time and location fixed effects which is closest to our main identification strategy and it shows a small and statistically insignificant relationship between s_{ot} and λ_{io} . Although earlier specifications yield statistically significant coefficients, their magnitudes remain economically negligible.

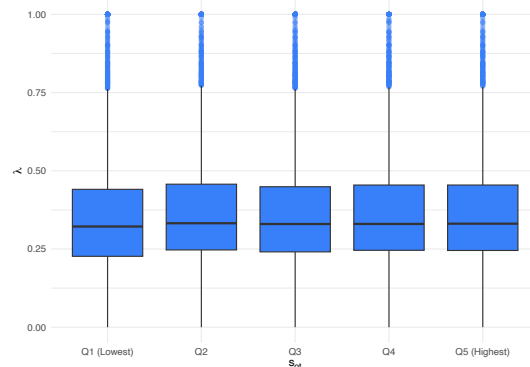
Table 3.A8: Relationship between propensity to migrate λ_{iot} and s_{ot}

	(1)	(2)	(3)	(4)
s_{ot}	0.00823*** (0.000995)	0.0103* (0.00564)	0.00675*** (0.00102)	0.0106 (0.00698)
x_{dt}	0.000749 (0.00122)	-0.000935 (0.00124)	0.00460*** (0.00135)	0.00256* (0.00138)
Observations	77140	77140	77140	77140
Year FE	No	Yes	No	Yes
Location FE	No	No	Yes	Yes

Notes: Data are from the Consumer Pyramids Household Survey (CPHS), 2014–2019. The dependent variable is the household's baseline propensity to migrate, λ_{io} . s_{ot} is the leave-one-out, distance-weighted export price shock at the origin district; x_{dt} is the destination “pull” shock index. Columns (1)–(4) add year and location (district) fixed effects as indicated. Standard errors, clustered at the district level, are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 3.A10 further corroborates this finding: it plots the distribution of λ_{io} by quintiles of s_{ot} and reveals no clear pattern. These results support the validity of our shift-share instrument by showing that the shock intensity is not mechanically related to baseline migration propensities.

Figure 3.A10: Distribution of migration propensity λ_{io} by quintile of s_{ot}



Notes: Data are from the Consumer Pyramids Household Survey (CPHS), 2014–2019. Box plots show the distribution of the household migration propensity, λ_{io} , within quintiles of the origin–district shock, s_{ot} . The box is the interquartile range, the line is the median, whiskers extend to 1.5 IQR, and dots are outliers.

3.A.12 Balance test of x_{dt} and s_{ot}

We conduct a series of balance tests to assess the validity of the exclusion restriction underlying our instrumental variable strategy. Specifically, we examine whether the labor demand shocks at the origin and destination (s_{ot} and x_{dt}) predict household or individual outcomes in the absence of migration. At the household level, we regress remittances on these shocks. We find no significant effect. At the individual level, we focus on working-age individuals and find no significant relationship between the shocks and key labor outcomes prior to treatment, including individual income, school enrollment, homemaker status, and labor force participation. These results suggest that the shocks are not correlated with pre-treatment household or individual characteristics, supporting the plausibility of the exclusion restriction and the validity of our identification strategy.

Table 3.A9: Balance tests of s_{ot} and x_{dt} on household and individual outcomes

	(1)	(2)	(3)	(4)	(5)
	Transfers	Econ Active	Homeworker	In school	Ind Income
s_{ot}	171.4 (139.4)	0.00494 (0.00664)	-0.00329 (0.00678)	0.00254 (0.00436)	35.27 (89.88)
x_{dt}	-67.41* (36.56)	0.00217 (0.00340)	0.00649** (0.00326)	0.00423* (0.00217)	58.70 (43.87)
Outcome Mean	538.5	0.296	0.200	0.123	3451.4
Treated HH/Ind	4610	2252	2252	2252	2252
Observations	75375	248553	248553	248553	248551

Notes: Data are from the Consumer Pyramids Household Survey (CPHS), 2014–2019. The table reports balance tests for the origin shock s_{ot} and the destination “pull” shock x_{dt} . Column (1) uses household-level remittance transfers (monthly rupees). Columns (2)–(5) use individual-level outcomes for working-age members (18–60): economically active, homemaker, in school, and monthly individual income (rupees). The sample is restricted to pre-migration observations for households that later separate; individual outcomes use members observed at home in the pre-period. All specifications include year and unit fixed effects. Standard errors, clustered at the district level, are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3.A.13 Characteristics of households that experience loss

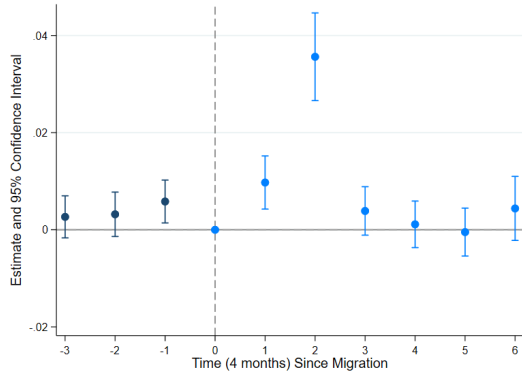
Table 3.A10: Households with mortality after separation

Covariate	No mortality	Mortality a year after	Difference
Unique HHs	4277	333	
Household income	16306.76 (13832.89)	15795.47 (13008.93)	-511.29
Household size	4.50 (1.54)	4.67 (1.72)	0.17
Share of females	0.43 (0.17)	0.43 (0.17)	0.00
Share of over 60 and under 18	0.36 (0.23)	0.35 (0.25)	-0.01
No working age members with complete high school	0.38 (0.51)	0.43 (0.53)	0.05
All working age member with complete high school	0.22 (0.44)	0.18 (0.42)	-0.04
Area: Urban very large	0.11 (0.31)	0.17 (0.37)	0.06**
Area: Urban large	0.14 (0.35)	0.15 (0.36)	0.01
Area: Urban median	0.19 (0.39)	0.19 (0.39)	-0.00
Area: Urban small	0.20 (0.40)	0.16 (0.37)	-0.04
Area: Rural	0.35 (0.48)	0.33 (0.47)	-0.02
Main occupation: Business/Entrepreneur	0.18 (0.40)	0.19 (0.41)	0.00
Main occupation: Salaried worker	0.18 (0.40)	0.18 (0.40)	-0.00
Main occupation: Farmers	0.10 (0.32)	0.12 (0.35)	0.02
Main occupation: Small traders	0.32 (0.48)	0.38 (0.50)	0.06*
Main occupation: Retired/student/home maker	0.18 (0.40)	0.10 (0.31)	-0.08***
Occupation: Missing data	0.01 (0.07)	0.01 (0.08)	0.00

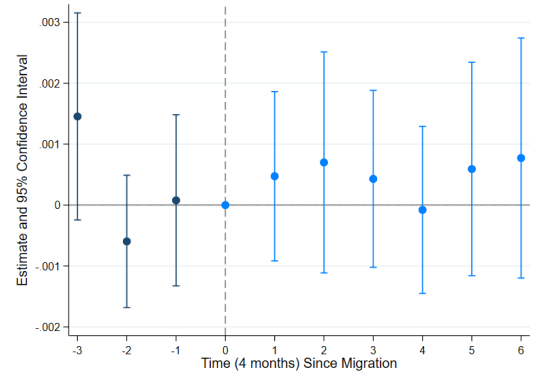
Notes: Data are from the CPHS, 2014–2019. The sample is households that experience separation due to migration of the male household head. “Mortality a year after” equals one if any household member dies within twelve months after separation; “No mortality” indicates no death in that window. Entries are means with standard deviations in parentheses (except “Unique HHs,” which is a count). “Difference” is Mortality minus No mortality, with standard errors in parentheses. Income is monthly rupees; shares range from 0 to 1. “Area” rows denote settlement-size categories; “Main occupation” rows refer to the household’s modal occupation group at baseline. Among 4,610 separated households, 333 report a death within one year. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3.B Results: Figures and Tables

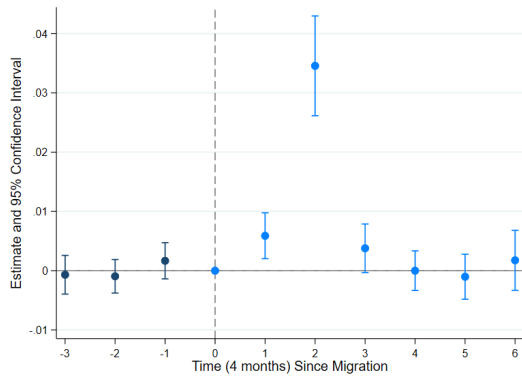
Figure 3.B11: Mortality of a household member



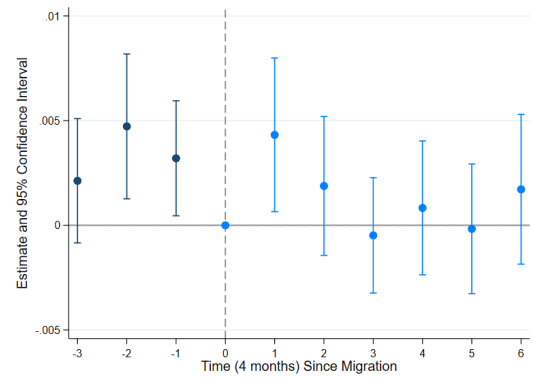
(a) Mortality of any member



(b) Mortality under 18



(c) Mortality between 18 - 65



(d) Mortality over 60

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot reports dynamic treatment effects estimated using the method of [de Chaisemartin and D'Haultfoeuille \(2023\)](#). The sample is comprised of households that experienced separation between 2014 and 2019, and it's matched control group. Estimates compare outcome changes for groups that transition from untreated to treated status at event time 1 to those that remain untreated over the same period, using the period immediately prior to separation as the baseline. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the treatment location. The dependent variables is 1 if a household member dies within the age range of the sub-figure. Table 3.B11 details the coefficients shown in the figures.

Table 3.B11: Event Study on Mortality of Household Members

	(1)	(2)	(3)	(4)	(5)
	Any member	Under 18	18-60	Over 60	Switchers
Placebos:					
Placebo _{t-1}	0.006*** (0.002)	0.000 (0.001)	0.002 (0.002)	0.003** (0.001)	4607
Placebo _{t-2}	0.003 (0.002)	-0.001 (0.001)	-0.001 (0.001)	0.005*** (0.002)	4165
Placebo _{t-3}	0.003 (0.002)	0.001* (0.001)	-0.001 (0.002)	0.002 (0.002)	3540
Effects:					
Effect _{t+1}	0.010*** (0.003)	0.000 (0.001)	0.006*** (0.002)	0.004** (0.002)	4610
Effect _{t+2}	0.036*** (0.005)	0.001 (0.001)	0.035*** (0.004)	0.002 (0.002)	4181
Effect _{t+3}	0.004 (0.003)	0.000 (0.001)	0.004* (0.002)	0.000 (0.001)	3822
Effect _{t+4}	0.001 (0.002)	0.000 (0.001)	0.000 (0.002)	0.001 (0.002)	3415
Effect _{t+5}	0.000 (0.003)	0.001 (0.001)	-0.001 (0.002)	0.000 (0.002)	3114
Effect _{t+6}	0.004 (0.003)	0.001 (0.001)	0.002 (0.003)	0.002 (0.002)	2796

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot presents dynamic treatment effects estimated using the method of [de Chaisemartin and D’Haultfoeuille \(2023\)](#). The sample includes households that experienced separation between 2014 and 2019. Estimates compare outcome changes for groups that transition from untreated to treated status at event time 1 to those that remain untreated during the same period, using the period immediately prior to separation as the reference. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variable in Column (1) is an indicator for whether any household member dies; in Column (2), the indicator refers to the death of a member under age 18; in Column (3), to a member aged 18–60; and in Column (4), to a member over age 60. Column (5) reports the number of treated households used in each estimation. mber of switchers corresponds to households that transition from non-separated to separated status (switchers-in) and are used to construct the event-time coefficients. The count declines at leads and lags farther from the event because fewer switchers have valid observations in all required pre- and post-treatment periods. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.B12: Event Study on Mortality of Household Members by Gender

	(1)	(2)	(3)	(4)	(5)
	18-60 Female	18-60 Male	Over 60 Female	Over 60 Male	Switchers
Placebos					
Placebo _{t-1}	0.002* (0.001)	0.000 (0.001)	-0.002 (0.002)	0.003 (0.002)	4607
Placebo _{t-2}	-0.001 (0.001)	-0.001 (0.001)	-0.002 (0.002)	0.005** (0.002)	4165
Placebo _{t-3}	-0.001 (0.001)	0.000 (0.001)	-0.001 (0.002)	0.001 (0.002)	3540
Effects					
Effect _{t+1}	0.004*** (0.001)	0.002 (0.001)	0.000 (0.002)	0.002 (0.002)	4610
Effect _{t+2}	-0.001 (0.001)	0.036*** (0.004)	-0.002 (0.002)	-0.002 (0.002)	4181
Effect _{t+3}	0.000 (0.001)	0.004*** (0.002)	-0.004* (0.002)	0.000 (0.002)	3822
Effect _{t+4}	-0.001 (0.001)	0.001 (0.001)	-0.002 (0.002)	-0.001 (0.002)	3415
Effect _{t+5}	-0.002 (0.001)	0.001 (0.002)	-0.004* (0.002)	-0.002 (0.002)	3114
Effect _{t+6}	0.000 (0.002)	0.003 (0.002)	-0.001 (0.002)	-0.002 (0.002)	2796

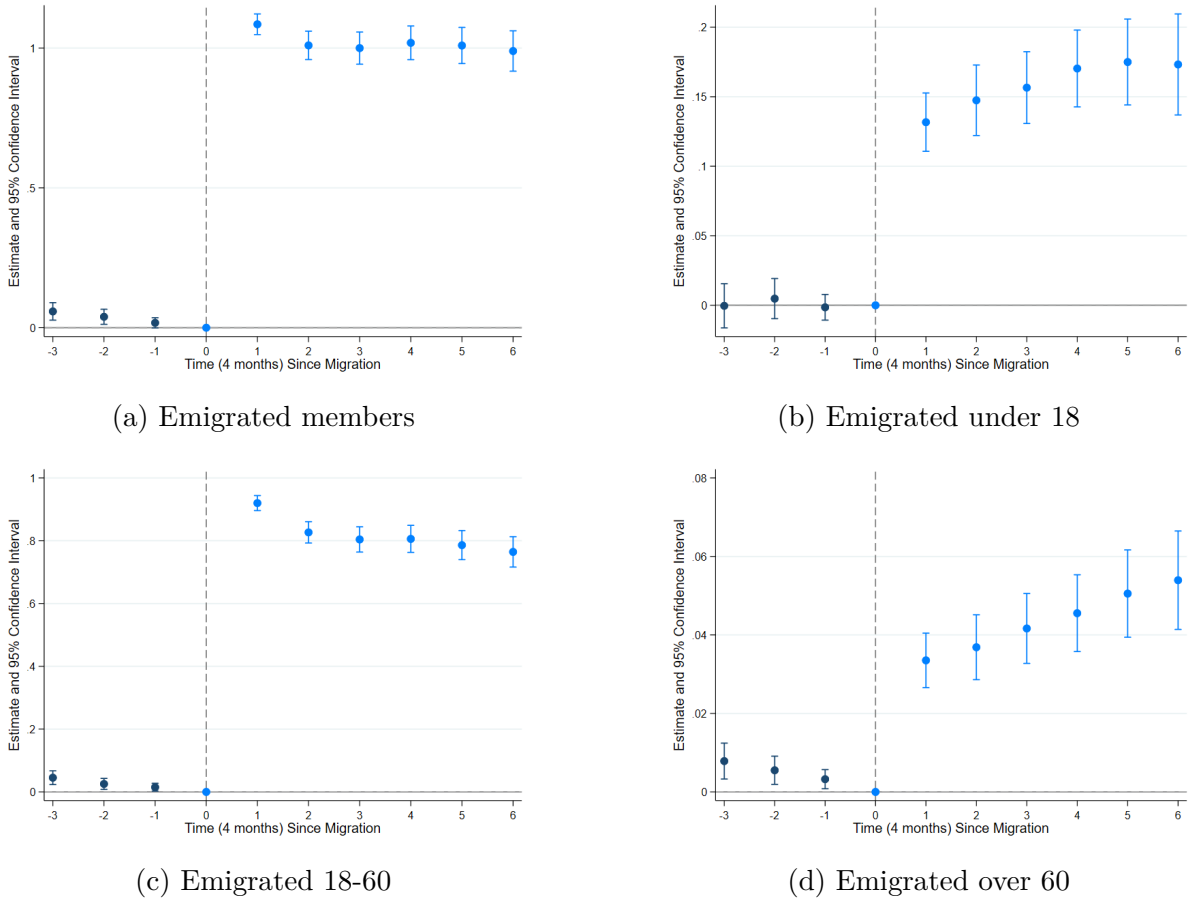
Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot presents dynamic treatment effects estimated using the method of [de Chaisemartin and D'Haultfoeuille \(2023\)](#). The sample includes households that experienced separation between 2015 and 2019. Estimates compare outcome changes for groups that transition from untreated to treated status at event time 1 to those that remain untreated during the same period, using the period immediately prior to separation as the reference. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variable in Column (1) is an indicator for whether any female household member between 18 and 60 years old dies; in Column (2), the indicator refers to the death of any male household member between 18 and 60 years; in Column (3), to a female member over 60; and in Column (4), to a male member over age 60. Column (5) reports the number of treated households used in each estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.B13: Second Stage: Mortality

	(1)	(2)	(3)	(4)
	Any Member	Under 18	18-60	Over 60
$\hat{Mig}_{iot}$	-0.0787 (0.0532)	-0.00888 (0.0157)	-0.0833** (0.0353)	0.0161 (0.0307)
Outcome Mean	0.0358	0.00319	0.0160	0.0160
KP (F-stat)	116.4	116.4	116.4	116.4
Treated Households	4610	4610	4610	4610
Observations	76936	76936	76936	76936

Notes: $\hat{Mig}_{iot}$ indicates if the household is separated in year t due to the migration of the male household head in district origin o instrumented by labor pull shock from exporting industries in destination districts. The dependent variable in Column (1) is an indicator for whether any household member died during year t . Column (2) restricts this to deaths among members under age 18, Column (3) to those aged 18–60, and Column (4) to members over age 60. All regressions include household and year fixed effects. Standard errors are clustered at the district level and reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 3.B12: Migration of household members



Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot reports dynamic treatment effects estimated using the method of [de Chaisemartin and D’Haultfoeuille \(2023\)](#). The sample is comprised of households that experienced separation between 2014 and 2019, and its matched control group. Estimates compare outcome changes for groups that transition from untreated to treated status at event time 1 to those that remain untreated over the same period, using the period immediately prior to separation as the baseline. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the treatment location. The dependent variable is 1 if a household member, that is not the household head or spouse, migrates within the age range of the sub figure. Table 3.B14 details the coefficients shown in the figures.

Table 3.B14: Event Study on Migration of Household Members

	(1)	(2)	(3)	(4)	(5)
	Any member	Under 18	18-60	Over 60	Switchers
Placebos:					
Placebo _{t-1}	0.017* (0.009)	-0.001 (0.005)	0.015** (0.006)	0.003*** (0.001)	4607
Placebo _{t-2}	0.039*** (0.014)	0.005 (0.007)	0.026*** (0.009)	0.006*** (0.002)	4165
Placebo _{t-3}	0.058*** (0.016)	0.000 (0.008)	0.045*** (0.011)	0.008*** (0.002)	3540
Effects:					
Effect _{t+1}	1.085*** (0.019)	0.132*** (0.011)	0.920*** (0.012)	0.034*** (0.004)	4610
Effect _{t+2}	1.010*** (0.026)	0.147*** (0.013)	0.827*** (0.017)	0.037*** (0.004)	4181
Effect _{t+3}	1.000*** (0.029)	0.157*** (0.013)	0.804*** (0.020)	0.042*** (0.005)	3822
Effect _{t+4}	1.019*** (0.031)	0.170*** (0.014)	0.806*** (0.022)	0.046*** (0.005)	3415
Effect _{t+5}	1.009*** (0.033)	0.175*** (0.016)	0.786*** (0.024)	0.051*** (0.006)	3114
Effect _{t+6}	0.990*** (0.037)	0.173*** (0.019)	0.764*** (0.025)	0.054*** (0.006)	2796

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot presents dynamic treatment effects estimated using the method of [de Chaisemartin and D’Haultfoeuille \(2023\)](#). The sample includes households that experienced separation between 2015 and 2019. Estimates compare outcome changes for groups that transition from untreated to treated status at event time 1 to those that remain untreated during the same period, using the period immediately prior to separation as the reference. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variable in Column (1) is an indicator for whether any household member migrates; in Column (2), the indicator refers to the migration of a member under age 18; in Column (3), to a member aged 18–60; and in Column (4), to a member over age 60. Column (5) reports the number of treated households used in each estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.B15: Event Study on Migration of Household Members - Long term separation

	(1)	(2)	(3)	(4)	(5)
	Any member	Under 18	18-60	Over 60	Switchers
Placebos:					
Placebo _{t-1}	0.049*** (0.015)	0.012 (0.009)	0.032*** (0.009)	0.004* (0.003)	1443
Placebo _{t-2}	0.104*** (0.024)	0.032** (0.013)	0.063*** (0.014)	0.005 (0.003)	1443
Placebo _{t-3}	0.173*** (0.033)	0.048*** (0.015)	0.107*** (0.022)	0.010** (0.004)	1443
Effects:					
Effect _{t+1}	1.280*** (0.034)	0.194*** (0.021)	1.042*** (0.020)	0.044*** (0.007)	1443
Effect _{t+2}	1.258*** (0.036)	0.196*** (0.023)	1.019*** (0.022)	0.047*** (0.007)	1443
Effect _{t+3}	1.215*** (0.040)	0.176*** (0.024)	0.999*** (0.025)	0.046*** (0.007)	1443
Effect _{t+4}	1.168*** (0.044)	0.163*** (0.025)	0.970*** (0.027)	0.043*** (0.008)	1443
Effect _{t+5}	1.135*** (0.049)	0.151*** (0.028)	0.952*** (0.031)	0.042*** (0.008)	1443
Effect _{t+6}	1.095*** (0.057)	0.144*** (0.030)	0.921*** (0.036)	0.040*** (0.008)	1443

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot presents dynamic treatment effects estimated using the method of [de Chaisemartin and D'Haultfoeuille \(2023\)](#). The sample includes households that experienced separation for six consecutive periods (two years) between 2015 and 2017. Estimates compare outcome changes for groups that transition from untreated to treated status at event time 1 to those that remain untreated during the same period, using the period immediately prior to separation as the reference. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variable in Column (1) is an indicator for whether any household member migrates; in Column (2), the indicator refers to the migration of a member under age 18; in Column (3), to a member aged 18–60; and in Column (4), to a member over age 60. Column (5) reports the number of treated households used in each estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.B16: Event Study on Total Household Income

	(1)	(2)	(3)	(4)	(5)
	Total income	Wages	Remittances	Household production	Switchers
Placebos:					
Placebo _{t-1}	-105.726 (309.023)	-386.683 (235.508)	-10.772 (33.263)	325.771 (217.453)	3387
Placebo _{t-2}	-200.638 (260.892)	-431.078* (259.359)	-57.614 (35.286)	294.711* (169.029)	2748
Placebo _{t-3}	-295.836 (302.353)	-457.488* (274.709)	-58.777 (46.681)	341.785* (187.895)	2271
Effects:					
Effect _{t+1}	-4235.394*** (250.240)	-6440.995*** (284.540)	2895.118*** (220.079)	-879.107*** (158.663)	3834
Effect _{t+2}	-4287.682*** (286.579)	-5207.957*** (331.960)	1759.416*** (177.429)	-919.749*** (205.662)	3152
Effect _{t+3}	-4148.636*** (340.513)	-4729.604*** (344.807)	1457.678*** (161.244)	-1032.219*** (205.534)	2790
Effect _{t+4}	-4008.822*** (346.821)	-4434.802*** (368.100)	1261.116*** (179.008)	-930.746*** (242.029)	2493
Effect _{t+5}	-3964.590*** (371.376)	-4166.052*** (353.734)	1149.777*** (179.683)	-945.716*** (227.939)	2285
Effect _{t+6}	-4131.333*** (373.615)	-4072.177*** (412.779)	1080.449*** (190.790)	-1307.597*** (265.363)	2017

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot presents dynamic treatment effects estimated using the method of [de Chaisemartin and D’Haultfoeuille \(2023\)](#). The sample includes households that experienced separation between 2014 and 2019. Estimates compare outcome changes for groups that transition from untreated to treated status at event time 1 to those that remain untreated during the same period, using the period immediately prior to separation as the reference. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variable in Column (1) is the total monthly income of the household at the origin; in Column (2), is the total income from wages; in Column (3) is the total income from remittances; and in Column (4), is the total income from household production (business or farms). Column (5) reports the number of treated households used in each estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.B17: Event Study on Total Household Income - Households with long term separation

	(1) Total income	(2) Wages	(3) Remittances	(4) Household production	(5) Switchers
Placebos:					
Placebo _{t-1}	-838.133** (424.579)	-773.837* (396.184)	-54.949 (43.041)	61.943 (251.592)	810
Placebo _{t-2}	-688.658 (445.508)	-532.947 (436.123)	-18.359 (40.374)	-119.528 (270.644)	810
Placebo _{t-3}	-1099.075** (480.991)	-981.858** (456.862)	7.341 (77.111)	-144.031 (275.699)	810
Effects:					
Effect _{t+1}	-4767.050*** (484.639)	-6026.838*** (495.215)	2467.973*** (416.296)	-1246.053*** (344.155)	810
Effect _{t+2}	-4285.738*** (494.263)	-5092.472*** (538.740)	1749.777*** (318.534)	-1076.568*** (385.641)	810
Effect _{t+3}	-4380.962*** (558.218)	-5012.942*** (523.600)	1514.066*** (315.167)	-996.311*** (329.906)	810
Effect _{t+4}	-4048.699*** (578.807)	-4766.323*** (538.326)	1251.970*** (320.978)	-621.888* (346.399)	810
Effect _{t+5}	-3574.142*** (655.375)	-3926.313*** (633.539)	1189.399*** (285.296)	-910.513*** (349.254)	810
Effect _{t+6}	-3704.021*** (593.277)	-3913.161*** (659.400)	1181.143*** (311.223)	-1047.085*** (401.979)	810

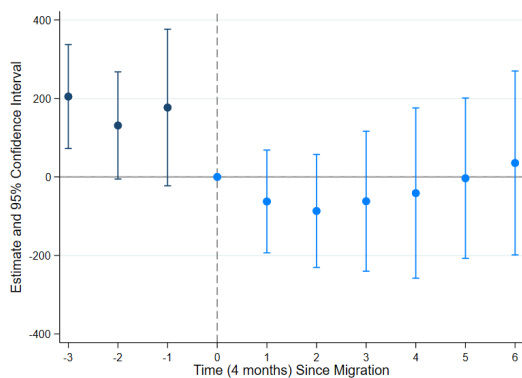
Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot presents dynamic treatment effects estimated using the method of [de Chaisemartin and D’Haultfoeuille \(2023\)](#). The sample includes households that experienced separation for six consecutive periods (two years) between 2015 and 2017. Estimates compare outcome changes for groups that transition from untreated to treated status at event time 1 to those that remain untreated during the same period, using the period immediately prior to separation as the reference. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variable in Column (1) is the total monthly income of the household at the origin; in Column (2), is the total income from wages; in Column (3) is the total income from remittances; and in Column (4), is the total income from household production (business or farms). Column (5) reports the number of treated households used in each estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.B18: Event Study on Total Household Income - Short term separation

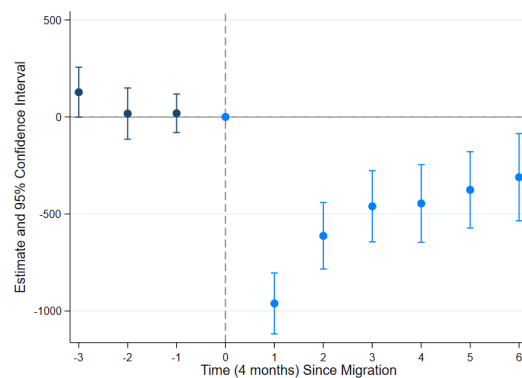
	(1) Total income	(2) Wages	(3) Remittances	(4) Household production	(5) Switchers
Placebos:					
Placebo _{t-1}	-834.888 (582.448)	-1011.644* (563.148)	-15.000 (61.451)	271.753 (252.046)	890
Placebo _{t-2}	-1087.501** (488.741)	-1170.983** (505.589)	-29.433 (71.040)	158.895 (307.878)	846
Placebo _{t-3}	-2126.901** (900.914)	-2253.159** (877.099)	-197.588 (141.050)	791.422* (479.194)	383
Effects:					
Effect _{t+1}	-4116.764*** (517.312)	-6648.161*** (496.346)	3174.176*** (290.892)	-906.484*** (334.992)	993
Effect _{t+2}	-3521.363*** (567.319)	-4114.614*** (615.346)	990.704*** (167.904)	-376.718 (361.400)	939
Effect _{t+3}	-2826.415*** (927.698)	-3024.826*** (948.749)	665.785*** (199.083)	-693.950 (431.225)	438

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot presents dynamic treatment effects estimated using the method of [de Chaisemartin and D’Haultfoeuille \(2023\)](#). The sample includes households that experienced separation for six consecutive periods (two years) between 2015 and 2017. Estimates compare outcome changes for groups that transition from untreated to treated status at event time 1 to those that remain untreated during the same period, using the period immediately prior to separation as the reference. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variable in Column (1) is the total monthly income of the household at the origin; in Column (2), is the total income from wages; in Column (3) is the total income from remittances; and in Column (4), is the total income from household production (business or farms). Column (5) reports the number of treated households used in each estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

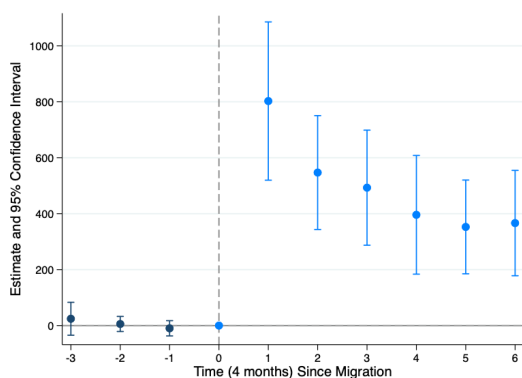
Figure 3.B13: Total income per capita



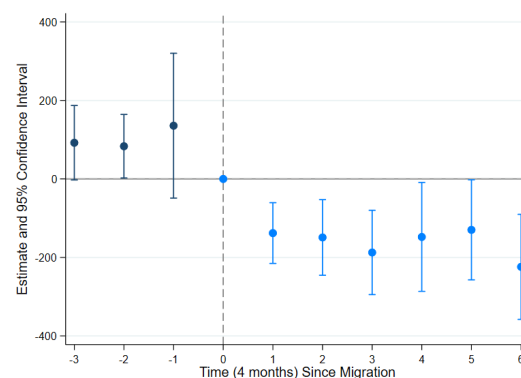
(a) Total income per capita



(b) Income from wages per capita



(c) Income from remittances per capita



(d) Income from household production per capita

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. The sample comprises households that experienced separation for six consecutive periods (two years) between 2015 and 2017. Estimates compare outcome changes for groups that transition from untreated to treated status at event time 1 to those that remain untreated over the same period, using the period immediately before separation as the baseline. The specification includes household and quadrimester fixed effects, and a time-varying control for household mortality. Standard errors are clustered at the treatment location. The dependent variable is the monthly household income per capita from each source. Table 3.B19 details the coefficients shown in the figures.

Table 3.B19: Event Study of Household Income per Capita

	(1) Income per capita	(2) Wages	(3) Remittances	(4) Household production	(5) Switchers
Placebos:					
Placebo _{t-1}	176.858* (101.752)	19.102 (50.549)	2.757 (12.821)	135.700 (94.144)	3387
Placebo _{t-2}	131.123* (69.635)	17.374 (67.359)	-10.307 (12.069)	83.352** (41.301)	2748
Placebo _{t-3}	204.849*** (67.580)	127.630* (65.719)	-2.487 (16.811)	92.242* (48.374)	2271
Effects:					
Effect _{t+1}	-62.520 (66.785)	-961.155*** (80.161)	918.339*** (67.658)	-137.958*** (39.435)	3834
Effect _{t+2}	-86.716 (73.507)	-612.531*** (87.363)	571.484*** (55.634)	-149.027*** (49.148)	3152
Effect _{t+3}	-61.848 (91.023)	-460.551*** (93.561)	469.797*** (52.034)	-187.403*** (54.809)	2790
Effect _{t+4}	-41.200 (110.661)	-445.796*** (102.171)	406.390*** (56.336)	-147.789** (70.726)	2493
Effect _{t+5}	-3.367 (104.243)	-375.759*** (100.414)	370.334*** (53.873)	-129.741** (65.049)	2285
Effect _{t+6}	35.593 (119.514)	-310.791*** (114.690)	339.877*** (59.209)	-223.943*** (68.233)	2017

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot presents dynamic treatment effects estimated using the method of [de Chaisemartin and D’Haultfoeuille \(2023\)](#). The sample and controls are the same as Table 3.B16. Standard errors are clustered at the district level. The dependent variable in Column (1) is the total monthly income of the household per members at the origin; in Column (2), is the income from wages per capita; in Column (3) is the income from remittances per capita; and in Column (4), is the total income from household production (business or farms) per capita. Column (5) reports the number of treated households used in each estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.B20: Event Study of Household Income per Capita - Long term separation

	(1)	(2)	(3)	(4)	(5)
	Income per capita	Wages	Remittances	Household production	Switchers
Placebos:					
Placebo _{t-1}	-86.357 (109.836)	-86.894 (99.726)	-9.860 (13.897)	5.778 (73.095)	810
Placebo _{t-2}	66.552 (108.816)	76.502 (108.452)	5.652 (13.766)	-48.110 (78.802)	810
Placebo _{t-3}	54.574 (113.492)	27.837 (114.674)	24.376 (30.031)	-33.242 (78.838)	810
Effects:					
Effect _{t+1}	-269.319* (149.538)	-872.445*** (160.018)	802.730*** (144.349)	-261.721** (118.363)	810
Effect _{t+2}	-241.210* (144.367)	-663.469*** (168.537)	547.043*** (103.851)	-223.346* (129.736)	810
Effect _{t+3}	-228.738 (165.928)	-617.553*** (168.307)	492.999*** (104.967)	-174.529 (112.097)	810
Effect _{t+4}	-106.518 (182.616)	-528.248*** (161.458)	395.982*** (108.238)	-76.158 (115.792)	810
Effect _{t+5}	-140.977 (169.550)	-452.449*** (173.056)	352.665*** (85.525)	-140.874 (113.209)	810
Effect _{t+6}	-102.710 (187.256)	-378.707* (200.026)	366.399*** (96.102)	-200.256 (123.042)	810

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot presents dynamic treatment effects estimated using the method of [de Chaisemartin and D'Haultfoeuille \(2023\)](#). The sample and controls are the same as Table 3.B16. Standard errors are clustered at the district level. The dependent variable in Column (1) is the total monthly income of the household per members at the origin; in Column (2), is the income from wages per capita; in Column (3) is the income from remittances per capita; and in Column (4), is the total income from household production (business or farms) per capita. Column (5) reports the number of treated households used in each estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.B21: Event Study of Household Income per Capita - Households with short term separation

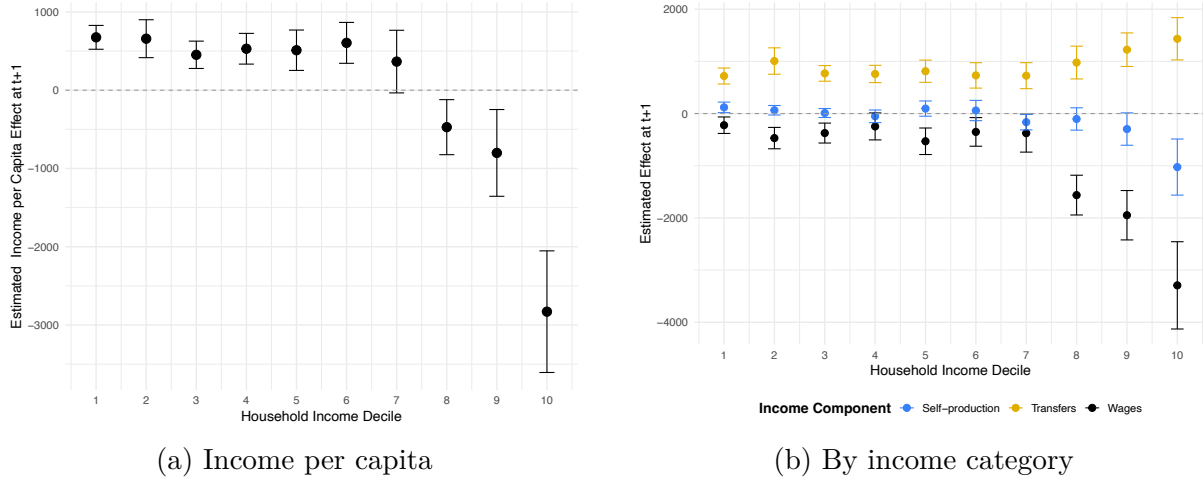
	(1) Income per capita	(2) Wages	(3) Remittances	(4) Household production	(5) Switchers
Placebos:					
Placebo _{t-1}	-54.769 (107.199)	-132.529 (100.280)	13.582 (20.843)	46.143 (64.840)	890
Placebo _{t-2}	-36.089 (127.083)	-153.730 (121.460)	16.345 (19.080)	27.502 (82.317)	846
Placebo _{t-3}	-247.691 (243.921)	-319.343 (221.891)	-2.261 (47.207)	74.926 (138.572)	383
Effects:					
Effect _{t+1}	-89.910 (148.291)	-1087.212*** (128.765)	1036.025*** (100.187)	-161.879** (80.526)	993
Effect _{t+2}	-122.009 (134.314)	-470.147*** (151.488)	312.689*** (52.236)	-8.110 (87.815)	939
Effect _{t+3}	163.041 (301.600)	-7.198 (329.631)	218.852*** (70.532)	-106.285 (127.063)	438

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot presents dynamic treatment effects estimated using the method of [de Chaisemartin and D’Haultfoeuille \(2023\)](#). The sample and controls are the same as Table 3.B16. Standard errors are clustered at the district level. The dependent variable in Column (1) is the total monthly income of the household per members at the origin; in Column (2), is the income from wages per capita; in Column (3) is the income from remittances per capita; and in Column (4), is the total income from household production (business or farms) per capita. Column (5) reports the number of treated households used in each estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.B22: Second Stage: Income per Capita

	(1)	(2)	(3)	(4)
	Total income	Wages	Remittances	HH Production
$\hat{Mig}_{iot}$	-361.3 (588.5)	-420.3 (531.4)	257.6** (127.8)	-165.5 (368.4)
Outcome Mean	4595.0	3440.6	187.4	793.0
KP (F-stat)	242.7	287.3	287.3	287.3
Treated Households	4610	4610	4610	4610
Observations	66698	75375	75375	75375

Notes: Mig_{iot} indicates if the household is separated in year t due to the migration of the male household head in district origin o instrumented by labor pull shock from exporting industries in destination districts. The dependent variable in Column (1) is the total monthly income earned by the household at the origin divided by the number of members in the household at origin ("per capita"). Column (2) reports total monthly wages per capita earned by household members. Column (3) captures total remittances and private transfers received by the household at the origin per capita. Column (4) measures total income from household production or business activities per capita. All regressions include household and year fixed effects. Standard errors are clustered at the district level and reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 3.B14: Net change in income per capita at $t+1$ after separation by baseline income

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. Effects at $t+1$ are estimated separately by deciles of baseline per capita income, defined in the period before separation for treated households and the matched period for controls. To retain sample size, we relax the panel-length requirement. Panel (a) reports the net change in income per capita; Panel (b) shows wages, transfers (remittances), and self-production components. Estimates use a DiD event study with individual and quadrimester fixed effects. Standard errors are clustered at the district level.

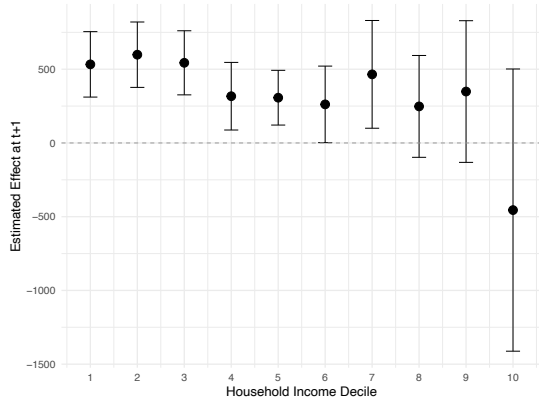
Table 3.B23: Event Study on Spouse's Economic Activity

	(1)	(2)	(3)	(4)	(5)	(6)
	Individual income	No income	Economically Active	Unpaid Work	In School	Switchers
Placebos:						
Placebo _{t-1}	36.516 (100.388)	-0.013 (0.009)	-0.005 (0.012)	0.006 (0.011)	0.005 (0.005)	717
Placebo _{t-2}	50.178 (102.070)	-0.012 (0.011)	-0.010 (0.013)	0.006 (0.012)	0.003 (0.004)	717
Placebo _{t-3}	29.115 (135.830)	0.002 (0.012)	-0.004 (0.013)	0.017 (0.015)	-0.001 (0.005)	717
Effects:						
Effect _{t+1}	652.607*** (146.904)	-0.090*** (0.015)	0.047*** (0.015)	-0.065*** (0.017)	-0.005 (0.005)	717
Effect _{t+2}	834.023*** (155.273)	-0.100*** (0.017)	0.085*** (0.017)	-0.071*** (0.018)	-0.004 (0.005)	717
Effect _{t+3}	940.189*** (186.553)	-0.096*** (0.020)	0.079*** (0.017)	-0.069*** (0.019)	-0.008 (0.005)	717
Effect _{t+4}	997.780*** (188.664)	-0.112*** (0.019)	0.089*** (0.018)	-0.081*** (0.020)	-0.002 (0.006)	717
Effect _{t+5}	854.635*** (182.198)	-0.098*** (0.019)	0.076*** (0.017)	-0.066*** (0.018)	-0.004 (0.005)	717
Effect _{t+6}	1011.726*** (210.624)	-0.095*** (0.018)	0.081*** (0.017)	-0.066*** (0.019)	0.001 (0.006)	717

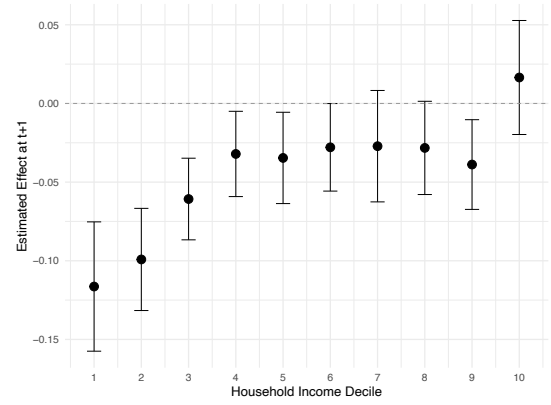
Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot presents dynamic treatment effects estimated using the method of [de Chaisemartin and D'Haultfoeuille \(2023\)](#). The sample includes households that experienced separation for six consecutive periods (two years) between 2015 and 2017. Estimates compare outcome changes for groups that transition from untreated to treated status at event time 1 to those that remain untreated during the same period, using the period immediately prior to separation as the reference. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variable in Column (1) is the total monthly individual income (in rupees); in Column (2), is an indicator if spouse has zero individual income; in Column (3) is an indicator for whether the spouse is economically active (working or unemployed and seeking work); and in Column (4), is an indicator for whether the spouse's main occupation is "homemaker." . In Column (5) is an indicator for student status as the spouse's main occupation. Column (6) reports the number of treated households used in each estimation.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

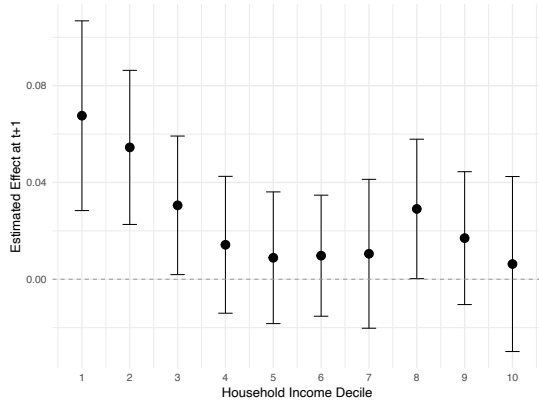
Figure 3.B15: Economic activity of female spouse at $t + 1$ by baseline income



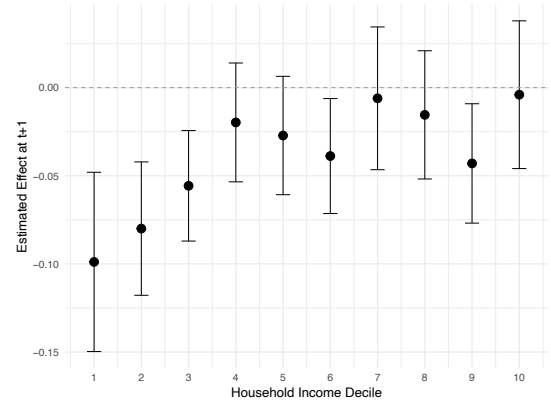
(a) Individual income



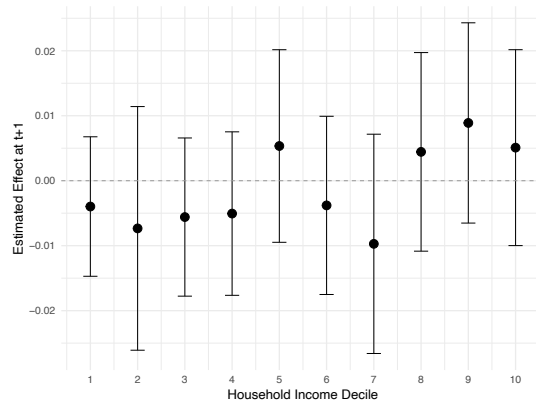
(b) No income



(c) Economically Active



(d) Unpaid Work (Homeworker)



(e) In School

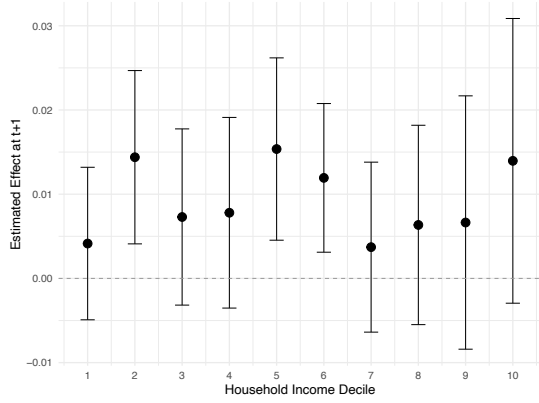
Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. Effects at $t+1$ are estimated by deciles of baseline per-capita income measured in the pre-separation wave for treated households and the matched period for controls. The sample is female spouses observed at home. Panel (a) reports monthly individual income (rupees); (b) zero-income indicator; (c) economically active (working or unemployed and seeking work); (d) homemaker as main occupation; (e) student as main occupation. Estimates use a DiD event study with individual and quadrimester fixed effects. Standard errors are clustered at the district level.

Table 3.B24: Event Study on Spouse's Occupation

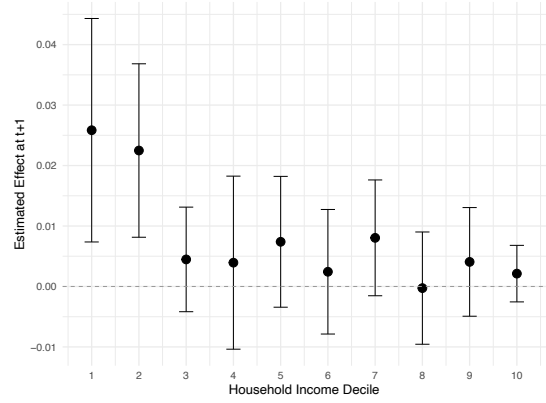
	(1)	(2)	(3)	(4)	(5)	(6)
	Business, Entrepreneur	Farmer	Small trader and Informal Worker	Other	Salaried worker and white collar worker	Switchers
Placebos:						
Placebo _{t-1}	0.000 (0.003)	0.003 (0.003)	-0.003 (0.006)	-0.001 (0.008)	0.001 (0.005)	698
Placebo _{t-2}	0.003 (0.004)	0.004 (0.003)	-0.010 (0.008)	0.001 (0.010)	0.002 (0.006)	698
Placebo _{t-3}	0.002 (0.004)	0.002 (0.003)	-0.012 (0.008)	0.006 (0.012)	0.002 (0.008)	698
Effects:						
Effect _{t+1}	0.013** (0.006)	0.010** (0.005)	0.024** (0.011)	-0.069*** (0.015)	0.023*** (0.008)	698
Effect _{t+2}	0.019*** (0.007)	0.010** (0.005)	0.032*** (0.012)	-0.080*** (0.016)	0.018* (0.010)	698
Effect _{t+3}	0.024*** (0.008)	0.010** (0.005)	0.039*** (0.013)	-0.086*** (0.017)	0.014* (0.008)	698
Effect _{t+4}	0.024*** (0.009)	0.012** (0.006)	0.047*** (0.013)	-0.100*** (0.018)	0.017** (0.008)	698
Effect _{t+5}	0.029*** (0.009)	0.013** (0.006)	0.036*** (0.012)	-0.087*** (0.017)	0.008 (0.008)	698
Effect _{t+6}	0.023*** (0.008)	0.008* (0.005)	0.044*** (0.012)	-0.089*** (0.017)	0.013* (0.008)	698

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot presents dynamic treatment effects estimated using the method of [de Chaisemartin and D'Haultfoeuille \(2023\)](#). The sample includes households that experienced separation for six consecutive periods (two years) between 2015 and 2017. Estimates compare outcome changes for groups that transition from untreated to treated status at event time 1 to those that remain untreated during the same period, using the period immediately prior to separation as the reference. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variable in Column (1) is an indicator for whether the spouse occupation is a business person or entrepreneur. In Column (2) dependent variable is an indicator if the spouse's occupation is farmer. In Column (3) the dependent variable is an indicator that corresponds to the occupation of small trader and informal workers. Column (4) corresponds to salaried employees and white-collar professional employees. Column (5) corresponds to other occupations including retirees, students and home makers. Column (6) reports the number of treated households used in each estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

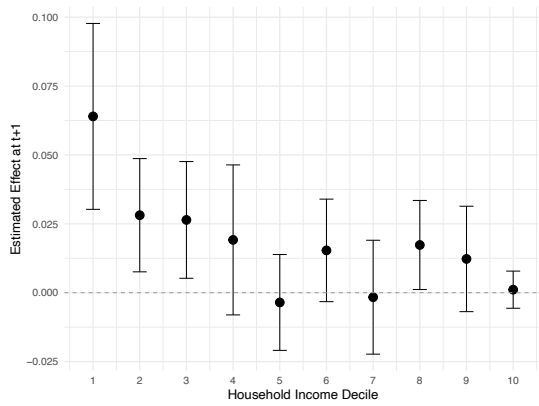
Figure 3.B16: Main occupation of female spouse at $t + 1$ by baseline income



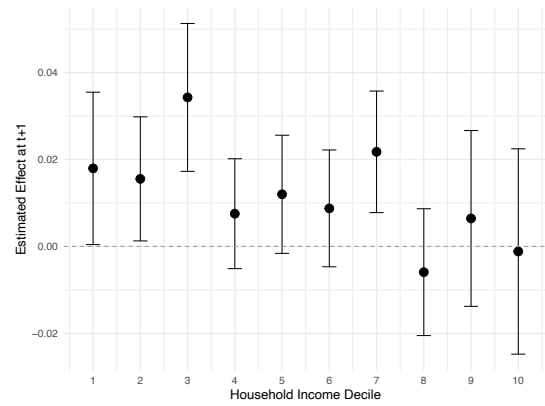
(a) Business/Entrepreneur



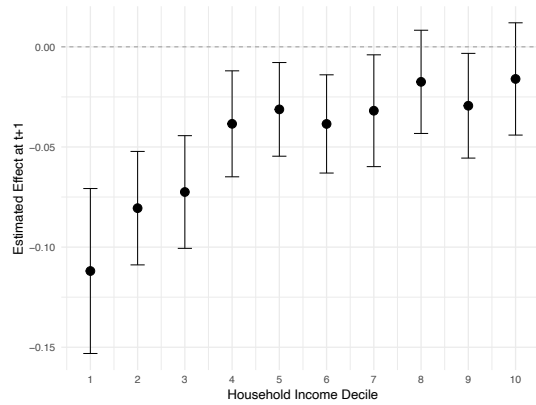
(b) Farmer



(c) Small trader and Informal worker



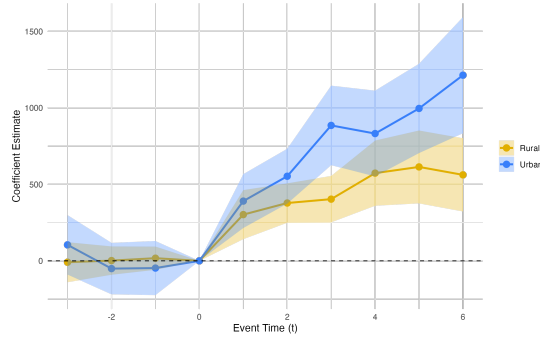
(d) Salaried/White collar professional



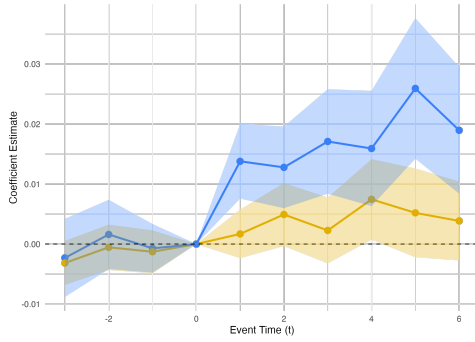
(e) Other

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. Effects at $t+1$ are estimated by deciles of baseline per capita income, measured in the pre-migration wave for treated households and the matched period for controls. The sample is female spouses observed at home. Each panel shows the effect on an indicator for the spouse's main occupation: (a) business/entrepreneur, (b) farmer, (c) small trader or informal worker, (d) salaried or white collar employee, and (e) other (includes homemaker, student, retired, or not working). Categories are mutually exclusive and exhaustive. Estimates use a difference in differences event study with individual and quadrimester fixed effects; standard errors are clustered at the district level.

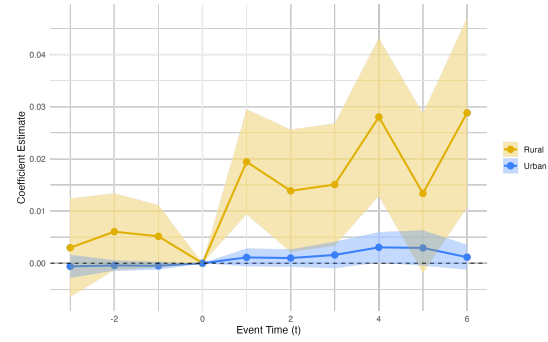
Figure 3.B17: Occupation of female spouse by region



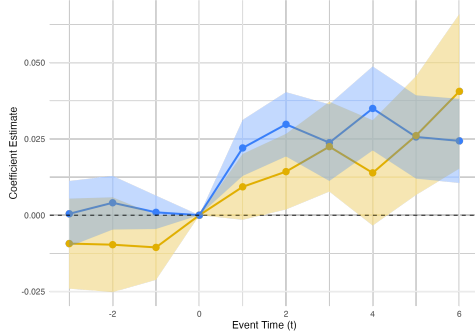
(a) Individual income



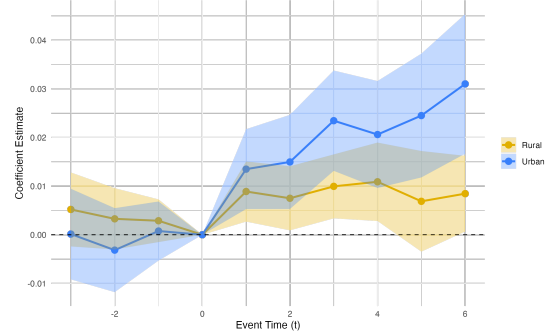
(b) Business/Entrepreneur



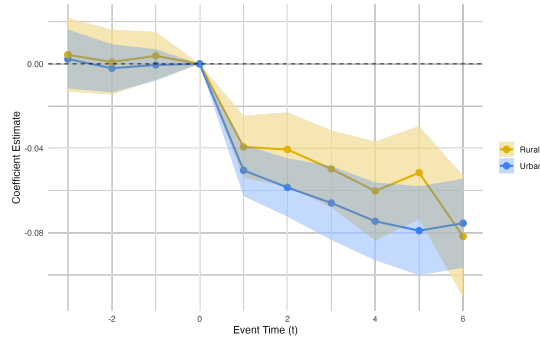
(c) Farmer



(d) Small trader and Informal worker



(e) Salaried/White collar professional



(f) Other

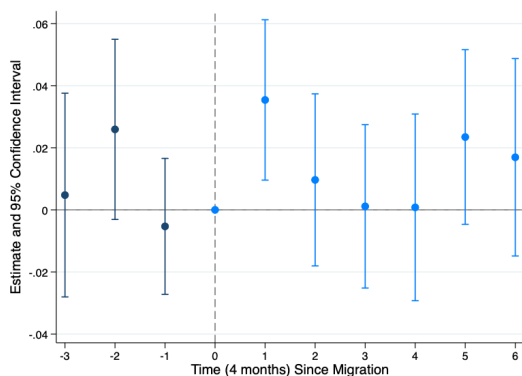
Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. Event-study estimates for female spouses by baseline region (rural vs. urban). Each panel plots effects by event time τ relative to the migration of the household head ($\tau = 0$). Outcomes are monthly individual income (a) and indicators for main occupation: business/entrepreneur (b), farmer (c), small trader or informal worker (d), salaried or white-collar employee (e), and other (f). Estimates include individual and quadrimester fixed effects; standard errors are clustered at the district level. Shaded areas are 95% confidence intervals.

Table 3.B25: Event Study on Working Age Males' Economic Activity

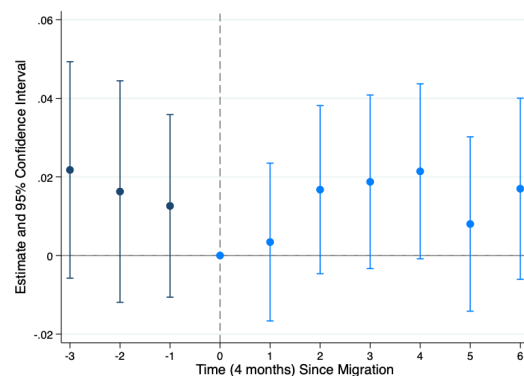
	(1)	(2)	(3)	(4)	(5)	(6)
	Individual income	No income	Economic Active	Home maker	Student	Switchers
Placebos:						
Placebo _{t-1}	-313.046 (251.172)	-0.001 (0.016)	0.013 (0.013)	-0.012* (0.007)	0.002 (0.010)	594
Placebo _{t-2}	117.687 (288.269)	-0.001 (0.019)	0.020 (0.014)	-0.011 (0.008)	-0.009 (0.008)	594
Placebo _{t-3}	142.746 (275.480)	-0.003 (0.017)	0.018 (0.016)	0.004 (0.009)	-0.013 (0.009)	594
Effects:						
Effect _{t+1}	612.084*** (232.721)	-0.030** (0.014)	0.032*** (0.010)	0.000 (0.007)	-0.033*** (0.008)	997
Effect _{t+2}	590.094** (237.430)	-0.029** (0.015)	0.046*** (0.011)	-0.011* (0.007)	-0.025*** (0.009)	997
Effect _{t+3}	731.317*** (270.167)	-0.033** (0.016)	0.034*** (0.013)	-0.005 (0.008)	-0.029*** (0.009)	997
Effect _{t+4}	933.381*** (288.042)	-0.033** (0.016)	0.041*** (0.013)	-0.011 (0.008)	-0.028*** (0.009)	997
Effect _{t+5}	997.217*** (337.961)	-0.037** (0.018)	0.052*** (0.014)	-0.010 (0.008)	-0.027*** (0.010)	997
Effect _{t+6}	904.191*** (342.574)	-0.036** (0.017)	0.051*** (0.013)	0.002 (0.009)	-0.031*** (0.009)	997

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot presents dynamic treatment effects estimated using the method of [de Chaisemartin and D'Haultfoeuille \(2023\)](#). The sample includes households that experienced separation for six consecutive periods (two years) between 2015 and 2017. Estimates compare outcome changes for groups that transition from untreated to treated status at event time 1 to those that remain untreated during the same period, using the period immediately prior to separation as the reference. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variable in Column (1) is the total monthly individual income (in rupees); in Column (2), is an indicator if the member has zero individual income; in Column (3) is an indicator for whether the member is economically active (working or unemployed and seeking work); and in Column (4), is an indicator for whether the member's main occupation is "homemaker." . In Column (5) is an indicator for member status as the spouse's main occupation. Column (6) reports the number of treated households used in each estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

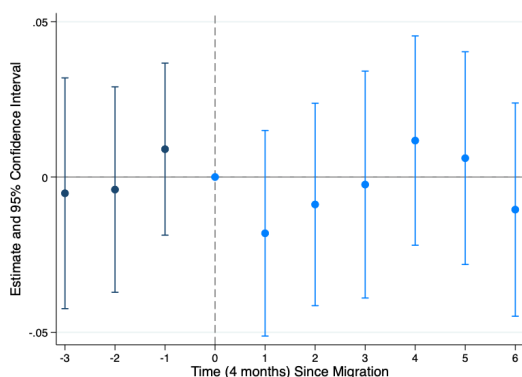
Figure 3.B18: Working-age Males' Occupation



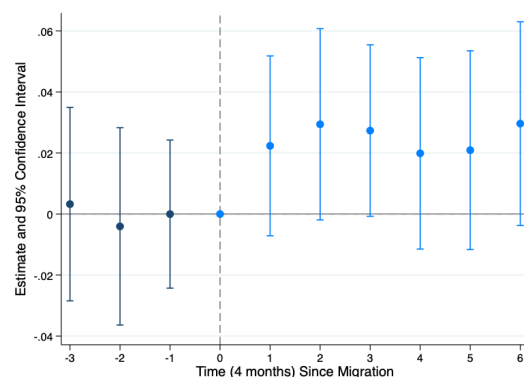
(a) Business/Entrepreneur



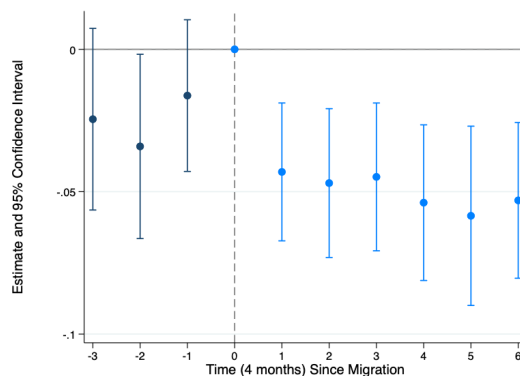
(b) Farmer



(c) Small trader and Informal worker



(d) Salaried/White collar professional



(e) Other

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot reports dynamic treatment effects using the sample selection and control group from Figure 3.1. Panel A shows an indicator for whether the member's occupation is a business person or entrepreneur, including business employees, entrepreneurs, qualified self-employed professionals, self-employed professionals and self-employed entrepreneurs. Panel B dependent variable is an indicator if the member's occupation is farmer, including organized farmers or small/marginal farmers. Panel C corresponds to the occupation of small trader and informal workers, including informal daily wage earners, home-based workers, hawkers, agricultural labourers, and wage labourers. Panel D corresponds to salaried employees including managers/supervisors, white-collar professional employees, white-collar clerical employees, non-industrial technical employees, industrial workers, support staff and legislators/social workers/activists. Panel E corresponds to other occupations including retirees, students and home makers. Table 3.B26 details the coefficients shown in the figures.

Table 3.B26: Event Study on Working-age Male Members' Occupation

	(1)	(2)	(3)	(4)	(5)	(6)
	Business, Entrepreneur	Farmer	Small trader and Informal Worker	Other	Salaried worker and white collar worker	Switchers
Placebos:						
Placebo _{t-1}	-0.008 (0.010)	0.002 (0.016)	0.019 (0.015)	-0.016 (0.017)	0.003 (0.012)	379
Placebo _{t-2}	0.019 (0.016)	0.007 (0.020)	0.000 (0.013)	-0.034* (0.020)	0.009 (0.015)	379
Placebo _{t-3}	-0.013 (0.015)	0.016 (0.015)	0.012 (0.017)	-0.021 (0.020)	0.006 (0.017)	379
Leads:						
Lead _{t+1}	0.031** (0.015)	0.004 (0.013)	-0.002 (0.016)	-0.059*** (0.015)	0.025 (0.015)	379
Lead _{t+2}	0.025 (0.015)	0.012 (0.012)	-0.021 (0.017)	-0.052*** (0.018)	0.036** (0.017)	379
Lead _{t+3}	0.030* (0.016)	0.023 (0.015)	-0.013 (0.021)	-0.074*** (0.018)	0.034* (0.019)	379
Lead _{t+4}	0.011 (0.015)	0.035*** (0.012)	0.010 (0.021)	-0.077*** (0.018)	0.020 (0.017)	379
Lead _{t+5}	0.043*** (0.015)	0.012 (0.015)	-0.006 (0.023)	-0.061*** (0.021)	0.012 (0.017)	379
Lead _{t+6}	0.028 (0.018)	0.012 (0.015)	0.005 (0.029)	-0.069*** (0.017)	0.025 (0.021)	379

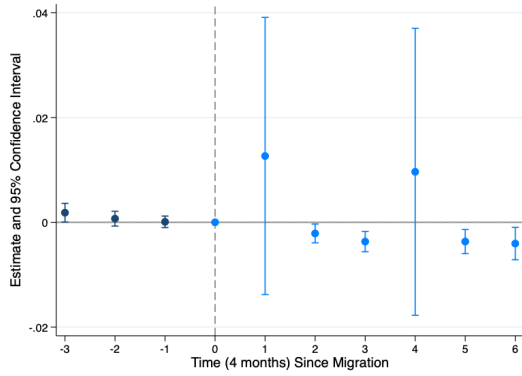
Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot presents dynamic treatment effects estimated using the method of [de Chaisemartin and D'Haultfoeuille \(2023\)](#). The sample includes households that experienced separation for six consecutive periods (two years) between 2015 and 2017. Estimates compare outcome changes for groups that transition from untreated to treated status at event time 1 to those that remain untreated during the same period, using the period immediately prior to separation as the reference. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variables in Column (1) is an indicator for whether the members' occupation is a business person or entrepreneur. In Column (2) dependent variable is an indicator if the members' occupation is farmer. In Column (3) the dependent variable is an indicator that corresponds to the occupation of small trader and informal workers. Column (4) corresponds to salaried employees and white-collar professional employees. Column (5) corresponds to other occupations including retirees, students and home makers. Column (6) reports the number of treated households used in each estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.B27: Event Study on Working Age Females' Economic Activity

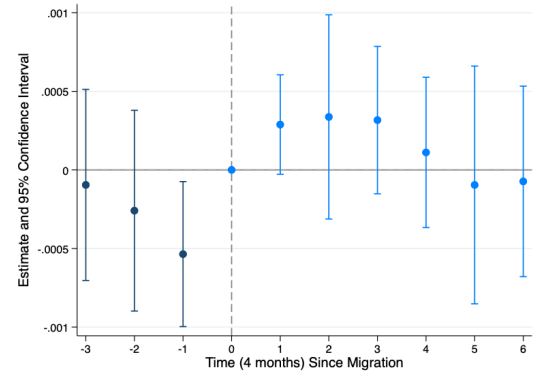
	(1)	(2)	(3)	(4)	(5)	(6)
	Individual income	No income	Economic Active	Home maker	Student	Switchers
Placebos:						
Placebo _{t-1}	408.252* (227.698)	-0.045* (0.025)	-0.058 (0.041)	-0.016 (0.075)	-0.010 (0.066)	45
Placebo _{t-2}	479.905** (226.324)	-0.067* (0.034)	-0.042 (0.042)	-0.008 (0.068)	-0.018 (0.065)	45
Placebo _{t-3}	310.920* (168.334)	-0.049 (0.033)	-0.019 (0.064)	0.021 (0.066)	-0.052 (0.063)	45
Effects:						
Effect _{t+1}	598.494* (349.447)	-0.091** (0.036)	0.051 (0.056)	-0.009 (0.057)	-0.092* (0.050)	75
Effect _{t+2}	802.717** (320.537)	-0.099** (0.040)	0.045 (0.066)	0.017 (0.065)	-0.114** (0.058)	75
Effect _{t+3}	1041.971** (512.793)	-0.083* (0.043)	-0.019 (0.052)	0.009 (0.061)	-0.102* (0.054)	75
Effect _{t+4}	1126.925* (647.758)	-0.082* (0.044)	0.018 (0.059)	0.003 (0.072)	-0.105* (0.055)	75
Effect _{t+5}	1591.171* (853.394)	-0.082** (0.037)	-0.001 (0.055)	0.008 (0.064)	-0.104* (0.056)	75
Effect _{t+6}	1017.528** (516.107)	-0.069** (0.034)	0.065 (0.053)	-0.034 (0.053)	-0.058 (0.046)	75

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot presents dynamic treatment effects estimated using the method of [de Chaisemartin and D'Haultfoeuille \(2023\)](#). The sample includes households that experienced separation for six consecutive periods (two years) between 2015 and 2017. Estimates compare outcome changes for groups that transition from untreated to treated status at event time 1 to those that remain untreated during the same period, using the period immediately prior to separation as the reference. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variable in Column (1) is the total monthly individual income (in rupees); in Column (2), is an indicator if the member has zero individual income; in Column (3) is an indicator for whether the member is economically active (working or unemployed and seeking work); and in Column (4), is an indicator for whether the member's main occupation is "homemaker." . In Column (5) is an indicator for member status as the spouse's main occupation. Column (6) reports the number of treated households used in each estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

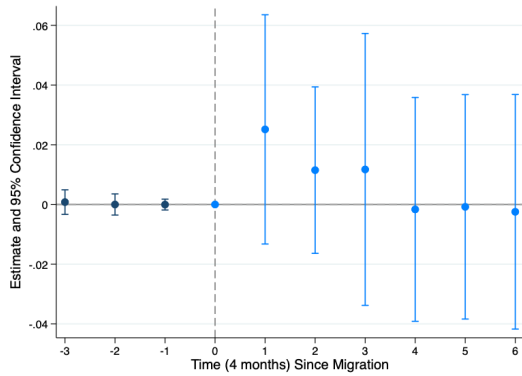
Figure 3.B19: Working-age Female's Occupation



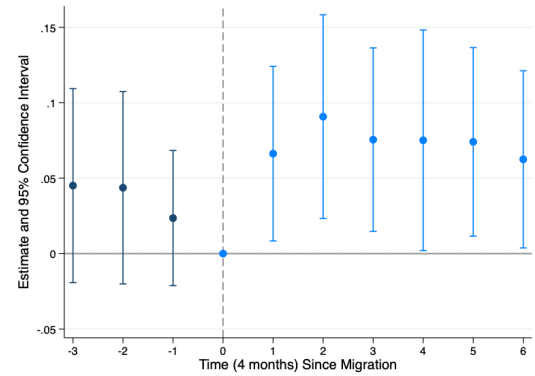
(a) Business/Entrepreneur



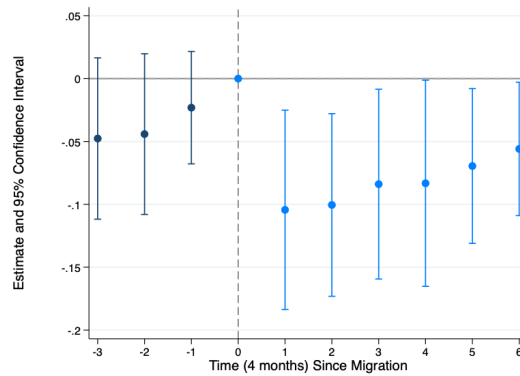
(b) Farmer



(c) Small trader and Informal worker



(d) Salaried/White collar worker



(e) Other

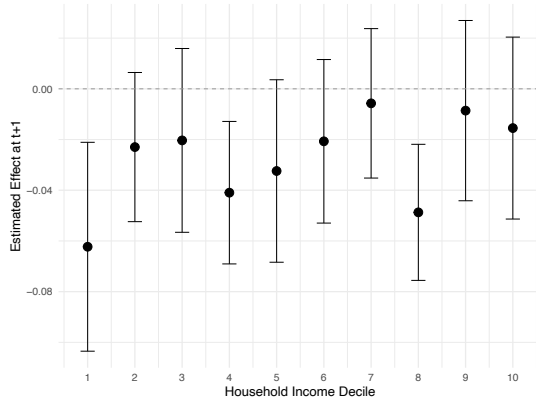
Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot reports dynamic treatment effects using the sample selection and control group from Figure 3.1. Panel A shows an indicator for whether the member's occupation is a business person or entrepreneur, including business employees, entrepreneurs, qualified self-employed professionals, self-employed professionals and self-employed entrepreneurs. Panel B dependent variable is an indicator if the member's occupation is farmer, including organized farmers or small/marginal farmers. Panel C corresponds to the occupation of small trader and informal workers, including informal daily wage earners, home-based workers, hawkers, agricultural labourers, and wage labourers. Panel D corresponds to salaried employees including managers/supervisors, white-collar professional employees, white-collar clerical employees, non-industrial technical employees, industrial workers, support staff and legislators/social workers/activists. Panel E corresponds to other occupations including retirees, students and home makers. Table 3.B28 details the coefficients shown in the figures.

Table 3.B28: Event Study on Working-age Female Members' Occupation

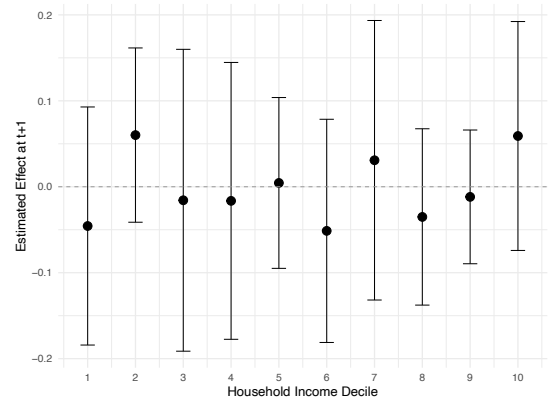
	(1)	(2)	(3)	(4)	(5)	(6)
	Business, Entrepreneur	Farmer	Small trader and Informal Worker	Other	Salaried worker and white collar worker	Switchers
Placebos:						
Placebo _{t-1}	0.000 (0.000)	-0.001*** (0.000)	0.000 (0.002)	-0.030 (0.032)	0.030 (0.032)	35
Placebo _{t-2}	0.001 (0.001)	0.000 (0.000)	0.000 (0.002)	-0.028 (0.031)	0.027 (0.032)	35
Placebo _{t-3}	0.002*** (0.001)	0.000 (0.000)	0.001 (0.002)	-0.032 (0.032)	0.029 (0.032)	35
Leads:						
Lead _{t+1}	0.027 (0.018)	0.000* (0.000)	0.026 (0.037)	-0.110** (0.043)	0.057** (0.029)	35
Lead _{t+2}	-0.003*** (0.001)	0.000 (0.000)	0.027 (0.039)	-0.050* (0.030)	0.026 (0.019)	35
Lead _{t+3}	-0.004*** (0.001)	0.000 (0.000)	0.026 (0.032)	-0.104 (0.080)	0.082 (0.061)	35
Lead _{t+4}	0.025 (0.037)	0.000 (0.000)	0.028 (0.032)	-0.163** (0.075)	0.110*** (0.042)	35
Lead _{t+5}	-0.003*** (0.001)	0.000 (0.000)	0.028 (0.033)	-0.077* (0.044)	0.052* (0.028)	35
Lead _{t+6}	-0.003** (0.001)	0.000 (0.000)	0.026 (0.017)	-0.048** (0.023)	0.025 (0.017)	35

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This event-study plot presents dynamic treatment effects estimated using the method of [de Chaisemartin and D'Haultfoeuille \(2023\)](#). The sample includes households that experienced separation for six consecutive periods (two years) between 2015 and 2017. Estimates compare outcome changes for groups that transition from untreated to treated status at event time 1 to those that remain untreated during the same period, using the period immediately prior to separation as the reference. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variables in Column (1) is an indicator for whether the members' occupation is a business person or entrepreneur. In Column (2) dependent variable is an indicator if the members' occupation is farmer. In Column (3) the dependent variable is an indicator that corresponds to the occupation of small trader and informal workers. Column (4) corresponds to salaried employees and white-collar professional employees. Column (5) corresponds to other occupations including retirees, students and home makers. Column (6) reports the number of treated households used in each estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

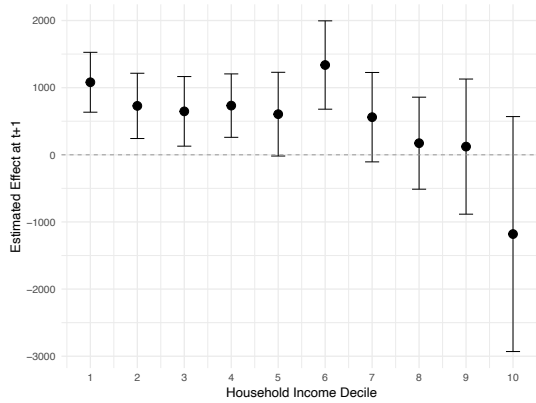
Figure 3.B20: Economic activity of working age members at $t + 1$ by baseline income



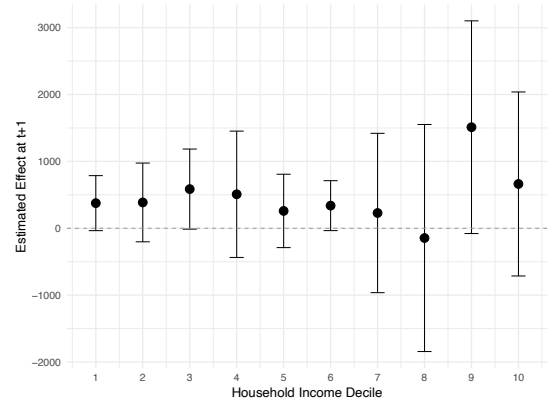
(a) In school - Male



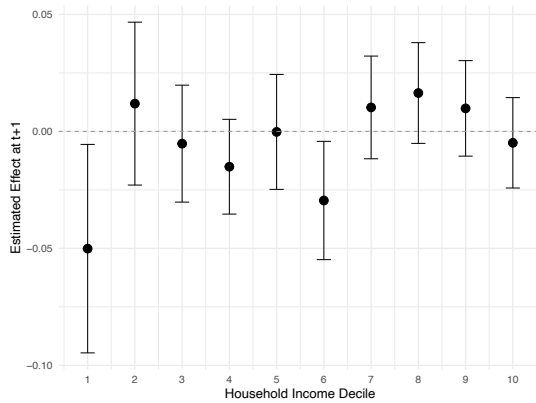
(b) In school - Female



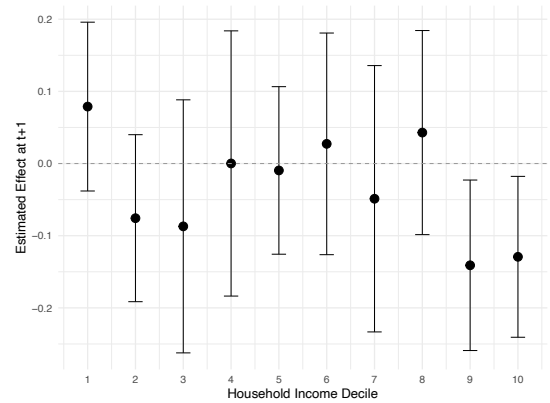
(c) Income - Male



(d) Income - Female



(e) Unpaid work - Male



(f) Unpaid work - Female

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. Effects at $t+1$ are estimated by deciles of baseline per-capita income, defined in the pre-migration wave for treated households and the matched period for controls. The sample includes working-age members (18–65) living at home and excludes the spouse of the migrant. Panels report: (a,b) in-school indicator; (c,d) monthly individual income (rupees); (e,f) unpaid work/homemaker indicator for males and females respectively. Estimates come from a DiD event study with individual and quadrimester fixed effects; standard errors are clustered at the district level.

Table 3.B29: Event Study on Household Asset Index and Appliances

	(1)	(2)	(3)	(4)	(5)	(6)
	Asset Index	Washing machines	Computers	Coolers	Refrigerators	Switchers
Placebos:						
Placebo _{t-1}	0.007 (0.013)	-0.004 (0.004)	0.003 (0.003)	0.003 (0.005)	0.000 (0.004)	1997
Placebo _{t-2}	0.006 (0.019)	-0.012* (0.006)	0.001 (0.004)	0.013** (0.006)	-0.001 (0.006)	1997
Placebo _{t-3}	-0.011 (0.022)	-0.016** (0.007)	0.000 (0.005)	0.015* (0.008)	-0.016** (0.008)	1997
Effects:						
Effect _{t+1}	-0.056*** (0.015)	-0.001 (0.005)	-0.003 (0.004)	-0.007 (0.006)	-0.006 (0.005)	2363
Effect _{t+2}	-0.077*** (0.021)	0.003 (0.006)	-0.008* (0.004)	-0.019** (0.008)	-0.009 (0.008)	2363
Effect _{t+3}	-0.067*** (0.025)	0.005 (0.007)	-0.006 (0.005)	-0.012 (0.010)	-0.011 (0.008)	2363
Effect _{t+4}	-0.072*** (0.027)	0.004 (0.008)	-0.010* (0.005)	0.007 (0.012)	-0.015 (0.010)	2363
Effect _{t+5}	-0.066** (0.028)	0.001 (0.008)	-0.012* (0.006)	0.014 (0.014)	-0.018** (0.009)	2363
Effect _{t+6}	-0.065** (0.031)	0.001 (0.009)	-0.010 (0.007)	0.013 (0.013)	-0.023** (0.010)	2363

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This table presents dynamic treatment effects estimated using the method of [de Chaisemartin and D'Haultfoeuille \(2023\)](#). The sample includes households that experienced separation due to male head migration for six consecutive periods (two years) between 2015 and 2017. The reference period is one quadrimester before separation. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variable in Column (1) is an asset index constructed using principal component analysis (PCA); Columns (2)–(5) report binary indicators for ownership of common household appliances. Column (6) reports the number of treated households used in each event time estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

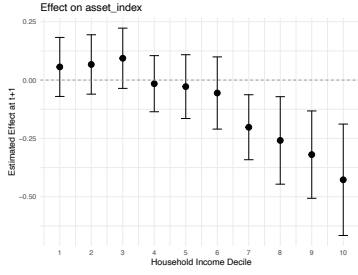
Table 3.B30: Event Study on Household Productive Assets

	(1) Tractors	(2) Cattle	(3) Generator	(4) Cars	(5) Two wheelers	(6) Switchers
Placebos:						
Placebo _{t-1}	0.001 (0.002)	0.010 (0.016)	-0.007* (0.004)	-0.002 (0.003)	0.013** (0.006)	1997
Placebo _{t-2}	0.000 (0.002)	0.017 (0.017)	-0.003 (0.006)	-0.002 (0.004)	0.015* (0.008)	1997
Placebo _{t-3}	-0.002 (0.002)	-0.007 (0.022)	-0.003 (0.008)	-0.006 (0.005)	0.017* (0.009)	1997
Effects:						
Effect _{t+1}	-0.002 (0.001)	-0.009 (0.014)	-0.001 (0.004)	-0.006* (0.003)	-0.038*** (0.008)	2363
Effect _{t+2}	0.001 (0.003)	-0.039** (0.019)	-0.004 (0.006)	-0.007 (0.004)	-0.056*** (0.009)	2363
Effect _{t+3}	-0.003 (0.002)	-0.037* (0.021)	-0.003 (0.007)	-0.008* (0.004)	-0.053*** (0.009)	2363
Effect _{t+4}	-0.003 (0.002)	-0.009 (0.022)	-0.011 (0.007)	-0.012** (0.005)	-0.058*** (0.010)	2363
Effect _{t+5}	-0.004* (0.002)	-0.005 (0.023)	-0.011 (0.008)	-0.009 (0.005)	-0.059*** (0.011)	2363
Effect _{t+6}	-0.005** (0.003)	0.007 (0.021)	-0.011 (0.009)	-0.010 (0.006)	-0.047*** (0.012)	2363

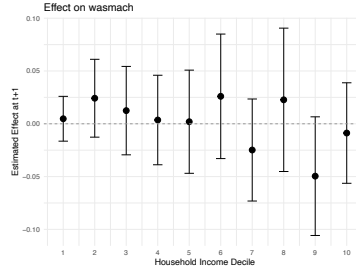
Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This table presents dynamic treatment effects estimated using the method of [de Chaisemartin and D’Haultfoeuille \(2023\)](#). The sample includes households that experienced separation due to male head migration for six consecutive periods (two years) between 2015 and 2017. The reference period is one quadrimester before separation. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variables are binary indicators for ownership of productive household assets: Column (1) reports ownership of tractors; Column (2) reports cattle ownership; Column (3) reports ownership of a generator; Column (4) reports car ownership; Column (5) reports ownership of two-wheelers. Column (6) reports the number of treated households used in each event time estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 3.B21: Assets at $t + 1$ by Baseline Income Decile

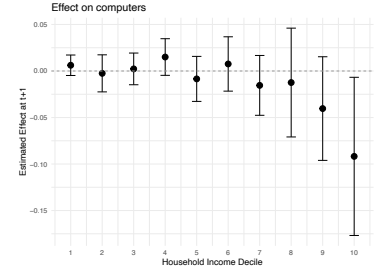
Asset Index and Appliances



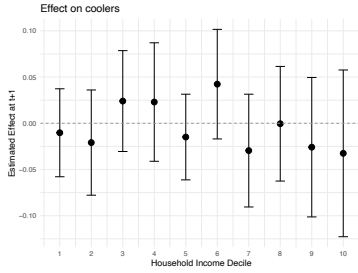
(a) Asset Index



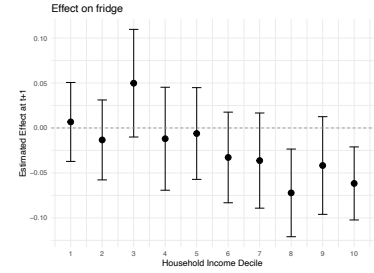
(b) Washing Machine



(c) Computers

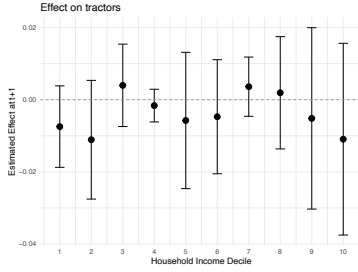


(d) Coolers

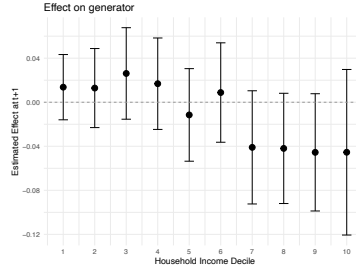


(e) Refrigerators

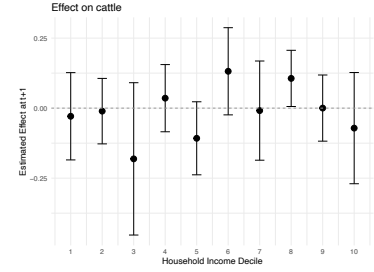
Productive Assets



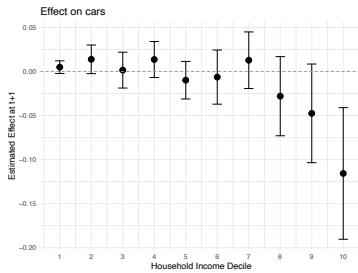
(f) Tractors



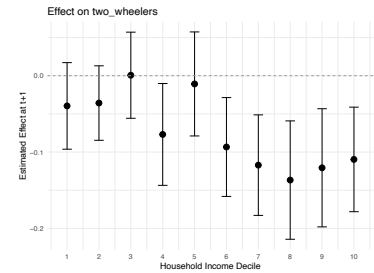
(g) Generators



(h) Cattle



(i) Cars



(j) Two Wheelers

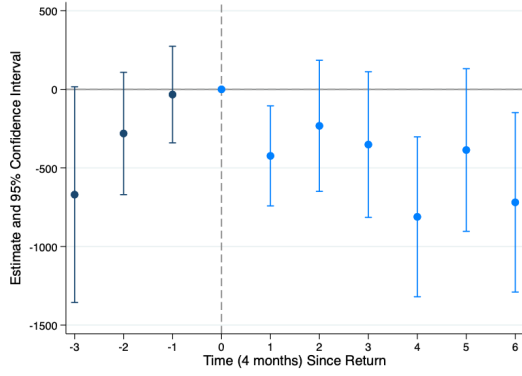
Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. Effects at $t+1$ are estimated separately by deciles of baseline per-capita income, defined in the pre-migration wave for treated households and the matched period for controls. The “Asset Index and Appliances” panels report a Asset index and indicators for owning washing machines, computers, coolers, and refrigerators. The “Productive Assets” panels report indicators for owning tractors, generators, cattle, cars, and two-wheelers. Estimates come from a DiD event study with household and quadrimester fixed effects; standard errors are clustered at the district level.

Table 3.B31: Event Study on Household Income after the Migrant Returns

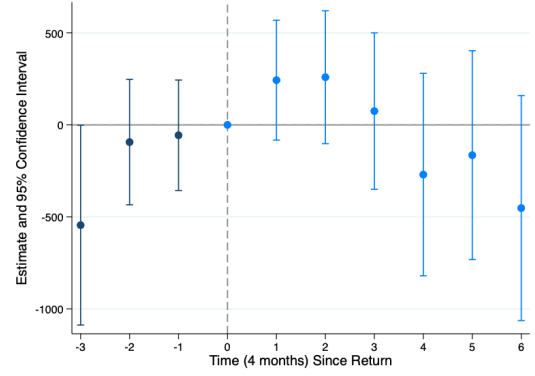
	(1) Total income	(2) Wages	(3) Remittances	(4) Household production	(5) Switchers
Placebos:					
Placebo _{t-1}	50.660 (456.929)	12.414 (470.536)	-33.790 (152.247)	323.984 (277.694)	746
Placebo _{t-2}	-510.465 (493.043)	62.192 (514.844)	-176.150 (180.037)	70.910 (444.378)	450
Placebo _{t-3}	-1063.694 (740.930)	-822.255 (668.640)	64.769 (271.022)	80.645 (593.339)	268
Effects:					
Effect _{t+1}	1415.036*** (523.421)	2717.215*** (525.323)	-1486.346*** (233.448)	303.983 (294.015)	1121
Effect _{t+2}	1994.500*** (590.211)	2872.640*** (554.083)	-1425.498*** (286.164)	839.261* (451.900)	903
Effect _{t+3}	2146.758*** (751.661)	2655.623*** (641.428)	-1144.331*** (276.038)	892.987 (564.641)	760
Effect _{t+4}	1611.349** (781.288)	1599.042** (698.187)	-744.747*** (246.055)	968.230* (553.880)	597
Effect _{t+5}	2483.516*** (942.351)	1687.429* (894.778)	-621.804*** (231.426)	1764.780** (789.127)	513
Effect _{t+6}	1957.537* (1023.823)	1297.418 (939.949)	-776.745*** (271.883)	1668.925* (854.532)	445

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This table presents dynamic treatment effects estimated using the method of [de Chaisemartin and D’Haultfoeuille \(2023\)](#). The sample includes households that experienced return migration to those that remain separated over the same horizon. The reference period is one quadrimester before reunification. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variables represent monthly total income (in rupees) in Column (1), total income from wages in Column (2), total income from remittances in Column (3) and total income from household production in Column (4). Column (5) reports the number of treated households used in each event time estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

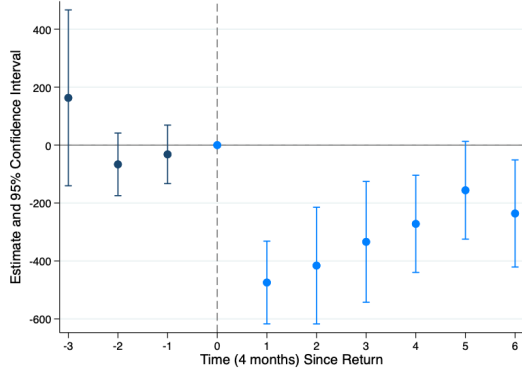
Figure 3.B22: Household Income per capita after the Migrant Returns



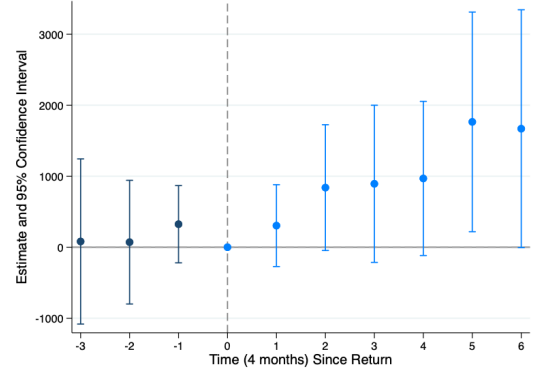
(a) Total Income



(b) Income from Wages



(c) Income from Remittances



(d) Income from Household Production

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This figure represents household income in per capita terms after the return of the male migrant household head. Panel A presents monthly total income (in rupees). Panel B reports total income from wages. Panel C shows total income from remittances. Panel D shows total income from household production. Table 3.B32 details the coefficients and controls shown in the figures.

Table 3.B32: Event Study on Income per Capita After the Migrant Returns

	(1) Income	(2) Wages	(3) Remittances	(4) Household Production	(5) Switchers
Placebos:					
Placebo _{t-1}	-33.098 (156.828)	-56.383 (153.106)	-31.914 (51.528)	101.496 (76.910)	746
Placebo _{t-2}	-280.795 (198.619)	-93.539 (173.875)	-66.420 (55.125)	11.479 (161.202)	450
Placebo _{t-3}	-670.034* (350.186)	-544.773** (276.976)	163.082 (154.858)	-36.783 (199.158)	268
Effects:					
Effect _{t+1}	-423.470*** (162.447)	242.977 (166.161)	-474.255*** (72.862)	-41.029 (90.013)	1121
Effect _{t+2}	-232.214 (212.893)	258.918 (184.252)	-415.822*** (102.752)	69.657 (138.273)	903
Effect _{t+3}	-351.525 (236.507)	74.898 (216.967)	-333.906*** (106.405)	3.145 (155.973)	760
Effect _{t+4}	-811.298*** (259.601)	-270.095 (280.606)	-271.769*** (85.571)	-111.067 (148.537)	597
Effect _{t+5}	-386.127 (264.006)	-164.412 (289.577)	-155.858* (86.073)	119.622 (209.638)	513
Effect _{t+6}	-719.054** (291.349)	-452.028 (311.964)	-235.949** (94.293)	113.384 (216.555)	445

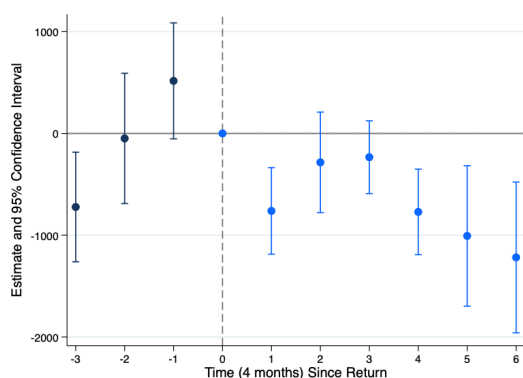
Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This table presents dynamic treatment effects estimated using the method of [de Chaisemartin and D'Haultfoeuille \(2023\)](#). The sample includes households that experienced return migration to those that remain separated over the same horizon. The reference period is one quadrimester before reunification. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variables represent monthly per capita measures of total income (in rupees) in Column (1), total income from wages in Column (2), total income from remittances in Column (3) and total income from household production in Column (4). Column (5) reports the number of treated households used in each event time estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.B33: Event Study on Spouse's Economic Activity after the Migrant Returns

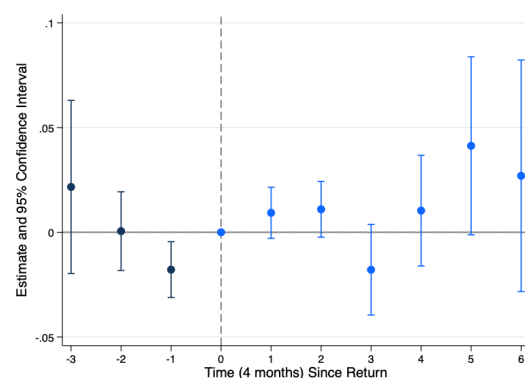
	(1)	(2)	(3)	(4)	(5)	(6)
	Individual Income	No income	Economic Active	Homemaker	In school	Switchers
Placebos:						
Placebo _{t-1}	-306.717* (163.889)	0.009 (0.011)	-0.003 (0.010)	0.012 (0.013)	0.002 (0.005)	863
Placebo _{t-2}	-155.242 (200.649)	-0.015 (0.015)	0.001 (0.014)	0.033** (0.016)	0.004 (0.006)	496
Placebo _{t-3}	-1021.008** (425.293)	0.015 (0.024)	-0.004 (0.023)	0.034 (0.024)	0.002 (0.004)	281
Effects:						
Effect _{t+1}	-381.547** (163.542)	0.039*** (0.010)	-0.035*** (0.010)	0.050*** (0.011)	-0.004 (0.004)	1349
Effect _{t+2}	-644.851*** (208.408)	0.063*** (0.012)	-0.051*** (0.013)	0.052*** (0.014)	0.001 (0.005)	1052
Effect _{t+3}	-661.052** (292.301)	0.060*** (0.015)	-0.042*** (0.014)	0.051*** (0.018)	0.003 (0.006)	867
Effect _{t+4}	-1067.838*** (321.896)	0.066*** (0.017)	-0.054*** (0.018)	0.071*** (0.021)	0.004 (0.006)	656
Effect _{t+5}	-843.729*** (295.569)	0.059*** (0.017)	-0.063*** (0.018)	0.053*** (0.020)	0.006 (0.006)	555
Effect _{t+6}	-945.302*** (297.463)	0.040* (0.022)	-0.052** (0.023)	0.042* (0.026)	0.002 (0.008)	477

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This table presents dynamic treatment effects estimated using the method of [de Chaisemartin and D'Haultfoeuille \(2023\)](#). The sample includes households that experienced return migration to those that remain separated over the same horizon. The reference period is one quadrimester before reunification. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variable in Column (1) is the total monthly individual income (in rupees) of the spouse; Column (2), is an indicator if the spouse has zero individual income; Column (3) is an indicator for whether the spouse is economically active (working or unemployed and seeking work); and Column (4), is an indicator for whether the spouse's main occupation is "homemaker." Column (5) is an indicator for spouse's main occupation as "school". Column (6) reports the number of treated households used in each estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

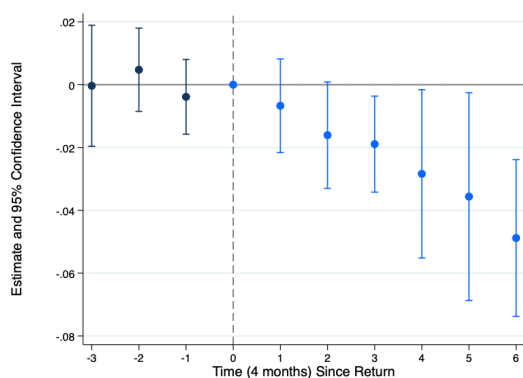
Figure 3.B23: Working-age Male's Economic Activity after the Migrant Returns



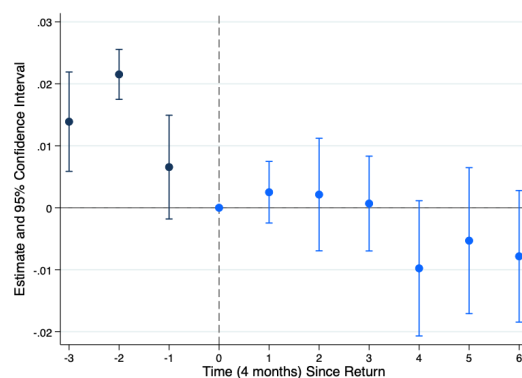
(a) Individual Income



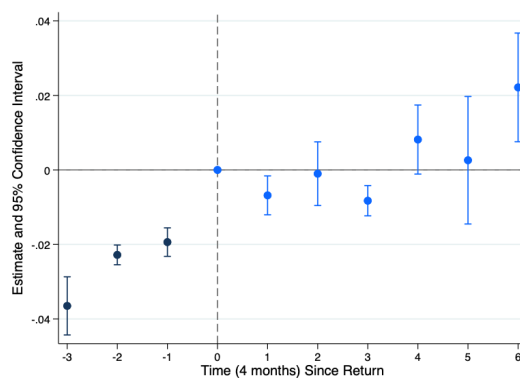
(b) No Income



(c) Economically Active



(d) Unpaid Work (Homemaker)



(e) In School

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This figure represents the economic activity of the working age male members after the return of the male migrant household head. Panel A presents monthly individual income (in rupees). Panel B reports whether the member has zero individual income. Panel C shows an indicator for whether the member is economically active (working or unemployed and seeking work). Panel D shows an indicator for whether the member is engaged in unpaid work i.e. her main occupation is “homemaker.” Panel E shows an indicator for student status as the member’s main occupation. Table 3.B34 details the coefficients and controls shown in the figures.

Table 3.B34: Event Study on Working Age Male's Economic Activity after the Migrant Returns

	(1)	(2)	(3)	(4)	(5)	(6)
	Individual Income	No income	Economic Active	Homemaker	In school	Switchers
Placebos:						
Placebo _{t-1}	516.331* (290.734)	-0.018*** (0.007)	-0.004 (0.006)	0.007 (0.004)	-0.019*** (0.002)	570
Placebo _{t-2}	-49.138 (326.785)	0.001 (0.010)	0.005 (0.007)	0.022*** (0.002)	-0.023*** (0.001)	344
Placebo _{t-3}	-723.122*** (274.794)	0.022 (0.021)	0.000 (0.010)	0.014*** (0.004)	-0.036*** (0.004)	221
Leads:						
Lead _{t+1}	-761.424*** (217.009)	0.009 (0.006)	-0.007 (0.008)	0.003 (0.003)	-0.007** (0.003)	866
Lead _{t+2}	-284.187 (251.893)	0.011 (0.007)	-0.016* (0.009)	0.002 (0.005)	-0.001 (0.004)	686
Lead _{t+3}	-233.409 (182.323)	-0.018 (0.011)	-0.019** (0.008)	0.001 (0.004)	-0.008*** (0.002)	575
Lead _{t+4}	-771.386*** (214.378)	0.010 (0.013)	-0.028** (0.014)	-0.010* (0.006)	0.008* (0.005)	428
Lead _{t+5}	-1007.349*** (352.163)	0.041* (0.022)	-0.036** (0.017)	-0.005 (0.006)	0.003 (0.009)	358
Lead _{t+6}	-1218.173*** (377.905)	0.027 (0.028)	-0.049*** (0.013)	-0.008 (0.005)	0.022*** (0.007)	321

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This table presents dynamic treatment effects estimated using the method of [de Chaisemartin and D'Haultfoeuille \(2023\)](#). The sample includes households that experienced return migration to those that remain separated over the same horizon. The reference period is one quadrimester before reunification. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variable in Column (1) is the total monthly individual income (in rupees); Column (2), is an indicator if the member has zero individual income; Column (3) is an indicator for whether the member is economically active (working or unemployed and seeking work); and Column (4), is an indicator for whether the member's main occupation is "homemaker." Column (5) is an indicator for members' main occupation as "school". Column (6) reports the number of treated households used in each estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.B35: Event Study on Household Asset Index and Appliances after The Migrant Returns

	(1)	(2)	(3)	(4)	(5)	(6)
	Asset Index	Washing machines	Computers	Coolers	Refrigerators	Switchers
Placebos:						
Placebo _{t-1}	0.015 (0.024)	0.001 (0.009)	-0.001 (0.005)	0.014 (0.009)	0.001 (0.007)	933
Placebo _{t-2}	0.020 (0.038)	0.011 (0.013)	-0.010 (0.010)	0.004 (0.017)	-0.002 (0.011)	585
Placebo _{t-3}	-0.064 (0.049)	0.006 (0.017)	-0.022 (0.014)	-0.030 (0.024)	-0.028* (0.016)	342
Leads:						
Lead _{t+1}	0.043* (0.023)	-0.008 (0.007)	0.001 (0.005)	0.014 (0.010)	0.002 (0.008)	1289
Lead _{t+2}	0.045 (0.031)	-0.023** (0.009)	-0.003 (0.008)	0.004 (0.015)	-0.008 (0.009)	1101
Lead _{t+3}	0.068* (0.037)	-0.008 (0.012)	-0.001 (0.009)	0.030* (0.017)	-0.007 (0.011)	923
Lead _{t+4}	0.034 (0.048)	-0.027* (0.015)	0.024* (0.014)	0.035* (0.019)	-0.012 (0.016)	723
Lead _{t+5}	0.050 (0.053)	-0.028 (0.018)	0.027 (0.016)	0.028 (0.022)	-0.012 (0.017)	623
Lead _{t+6}	0.073 (0.059)	-0.029 (0.020)	0.030* (0.018)	0.046* (0.026)	0.003 (0.019)	528

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This table presents dynamic treatment effects estimated using the method of [de Chaisemartin and D'Haultfoeuille \(2023\)](#). The sample includes households that experienced return migration to those that remain separated over the same horizon. The reference period is one quadrimester before reunification. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variable in Column (1) is an asset index constructed using principal component analysis (PCA); Columns (2)–(5) report binary indicators for ownership of common household appliances. Column (6) reports the number of treated households used in each event time estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.B36: Event Study on Household Productive Assets after The Migrant Returns

	(1) Tractors	(2) Cattle	(3) Generator	(4) Cars	(5) Two wheelers	(6) Switchers
Placebos:						
Placebo _{t-1}	0.000 (0.002)	0.021 (0.043)	0.001 (0.007)	0.004 (0.004)	-0.010 (0.011)	933
Placebo _{t-2}	0.002 (0.003)	0.027 (0.046)	-0.010 (0.012)	0.014* (0.009)	0.019 (0.017)	585
Placebo _{t-3}	-0.008 (0.005)	-0.038 (0.058)	-0.007 (0.015)	0.003 (0.009)	-0.030 (0.024)	342
Leads:						
Lead _{t+1}	0.003 (0.003)	-0.011 (0.021)	0.006 (0.006)	0.011* (0.006)	0.031** (0.013)	1289
Lead _{t+2}	0.008** (0.004)	-0.003 (0.029)	0.009 (0.009)	0.026*** (0.009)	0.035** (0.015)	1101
Lead _{t+3}	0.009** (0.004)	0.019 (0.042)	0.001 (0.010)	0.026*** (0.010)	0.028 (0.018)	923
Lead _{t+4}	0.004 (0.005)	-0.015 (0.041)	-0.010 (0.012)	0.022* (0.012)	0.022 (0.019)	723
Lead _{t+5}	0.005 (0.006)	0.019 (0.051)	0.016 (0.016)	0.010 (0.014)	0.012 (0.021)	623
Lead _{t+6}	0.005 (0.007)	0.071 (0.055)	0.021 (0.019)	0.010 (0.014)	0.008 (0.026)	528

Notes: Data from the Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring the Indian Economy (CMIE), spanning 2014–2019. This table presents dynamic treatment effects estimated using the method of [de Chaisemartin and D’Haultfoeuille \(2023\)](#). The sample includes households that experienced return migration to those that remain separated over the same horizon. The reference period is one quadrimester before reunification. The specification includes household and quadrimester fixed effects. Standard errors are clustered at the district level. The dependent variables are binary indicators for ownership of productive household assets: Column (1) reports ownership of tractors; Column (2) reports cattle ownership; Column (3) reports ownership of a generator; Column (4) reports car ownership; Column (5) reports ownership of two-wheelers. Column (6) reports the number of treated households used in each event time estimation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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