Immigration and Firm Investment*

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November 13, 2026

Abstract

In neoclassical models of immigration's long-run effects, capital adjustment shields incumbent workers from losses by counteracting the decline in the marginal productivity of labor. This paper argues that, by inhibiting this adjustment, credit-market frictions amplify the negative wage and employment effects of immigration. I develop a model in which monopsonistic firms with higher initial debt burdens face endogenously steeper financing-cost curves. As a result, immigrant inflows decrease capital intensity, wages, and native employment by more at initially higher-leverage firms. I test these predictions using a custom link between German firms' financial statements and social security records. I first document that, in Germany during the 2010s, a large immigration shock coincided with a sharp decline in firms' capital intensity, and that the borrowing costs of initially higher-leverage firms were more sensitive to additional debt. Exploiting variation in the settlement patterns of earlier immigrants, I find that firms' immigrant hiring responses did not vary by their initial leverage. However, initially higher-leverage firms experienced sharper declines in their capital intensity, wages, and native employment, consistent with my model's predictions. My results imply that credit-market frictions are an underexplored determinant of how the economy absorbs labor supply shocks.

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*Author contact: ararat.gocmen.19@ucl.ac.uk. I thank my advisors Christian Dustmann, Uta Schönberg, and Saleem Bahaj for their guidance. I also thank for their helpful comments and suggestions Clara Martínez-Toledano, Cevat Giray Aksoy, Alan Blinder, Christina Brinkmann, Wendy Carlin, Pauline Carry, Thomas Cornelissen, Ellora Derenoncourt, Andrew Ellul, Britta Glennon, David Green, Vishan Nigam, Marco Pagano, Christopher Palmer, Sukrit Puri, Imran Rasul, Raffaele Saggio, Anna Stansbury, Mathias Thoenig, Emil Verner, Ning Zhang, Floris Zoutman, and participants at the UCL Applied Economics and Finance Seminars, Universidad Carlos III de Madrid ENTER Seminar, Norwegian Centre for Taxation Seminar, Armenian Economic Association Annual Meeting, Armenian Economic Association Young Scholar Workshop, Asia Meeting of the Econometric Society-China, CSEF-CEPR Conference on Labor and Finance, ESMT Berlin and IWH Labor and Finance Group Fall Conference, Migration and Organizations Conference, RFBerlin Migration Forum, RFBerlin Nizza Monferrato Workshop, and UCL SPP Migration Cluster and ETH Immigration Policy Lab Workshop on Immigration and Political Behavior. I acknowledge financial support from the James M. and Cathleen D. Stone Centre on Wealth Concentration, Inequality, and the Economy at UCL. This paper was awarded the Best Paper Award in Labor and Public Economics at the Asia Meeting of the Econometric Society-China in 2026.

1 Introduction

Over 50 million immigrants arrived in the United States, Canada, and the European Union over the past decade (OECD, 2025).[1] In this context, the economic effects of immigration have become the subject of contested political discourse (IOM, 2026). In these debates, economists have often emphasized that, since firms combine capital with labor, capital adjustment over sufficiently long horizons may shield incumbent workers from losses due to labor market competition with immigrants (Borjas, 2003; Card, 2009; Lewis, 2011; Ottaviano and Peri, 2012; Dustmann et al., 2017).

Yet little attention has been paid to capital-market frictions that, even over long horizons, risk constraining this adjustment. Even when *aggregate* capital supply is perfectly elastic, as in neoclassical models of immigration's long-run effects (Lewis, 2013; Dustmann and Schönberg, 2025), an individual *firm*'s financing costs may exceed market interest rates (Cavalcanti et al., 2024) and be sensitive to adjustments of its capital stock. While the steepness of firms' financing-cost curves has been shown to shape the economy's responses to consumer demand (Giroud and Mueller, 2017) and monetary policy shocks (Ottonello and Winberry, 2020; Bahaj et al., 2022; Anderson and Cesa-Bianchi, 2024), its importance in understanding shocks to complementary factors—such as immigration-induced increases in labor supply—remains comparatively unexplored.

In this paper, I show that credit-market frictions constrain how firms' capital intensities adjust to immigration shocks and, thus, amplify the negative wage and employment effects of immigration. To explore these frictions both theoretically and empirically, I develop a model in which differences in initial debt burdens lead firms to differ in the sensitivity of their financing costs to adjustments of their capital stocks (Bernanke et al., 1999). Embedding this microfoundation for heterogeneous capital supply elasticities into a partial-equilibrium model of monopsonistic labor markets (Dustmann and Schönberg, 2025), I predict that firm leverage is a key moderator of firms' responses to an immigration-induced increase in local labor supply. In particular, firms with high leverage prior to immigration face steeper financing-cost curves, so their capital intensity, wages, and native employment fall by more in response to immigration.

To test these predictions, I use a custom link between German firms' financial statements and social security records. I first provide descriptive evidence that, coinciding with a large immigration shock during the 2010s, German firms' capital intensity declined sharply, especially among firms with high initial leverage. The borrowing costs of these initially high-leverage firms were also more sensitive to additional debt.

[1] This number is calculated based on Table A.1 of the latest *International Migration Outlook* (OECD, 2025), which reports the inflows of foreign nationals into selected countries from 2014 to 2023.

I then estimate firm-level effects of market-level immigration shocks across the 2010 leverage distribution, using immigrants' settlement patterns in 1993 as instruments for immigration into local labor markets from 2010 to 2019. I find that firms hired immigrants regardless of their initial leverage. Unlike other dimensions of firm heterogeneity, such as age and size, along which I find that immigrants did sort across firms, leverage thus did not limit firms' hiring of immigrants. However, capital intensity, wages, and native employment fell more sharply at the initially highest-leverage firms than at lower-leverage ones. Large initial debt burdens therefore seem to have constrained firms' investment responses to an immigration-induced increase in labor supply, with costly consequences for their incumbent workers.

These findings suggest that the economy's ability to absorb immigration shocks depends not only on how much capital is available in aggregate. It also depends on whether the firms that hire immigrants are able to obtain the financing necessary to adjust their capital stocks. Immigration's effects on incumbent workers may therefore vary with the state of firms' balance sheets at the time of immigrants' arrival: the same inflow could have more adverse effects when it coincides with high leverage than when firms have room to borrow. Policies that ease access to credit for constrained firms may thus complement immigration policy in mitigating incumbent workers' losses.

Model. My analysis proceeds in four steps. First, I develop a partial-equilibrium model of the labor market effects of immigration that allows for firm heterogeneity in capital-market frictions. This is in contrast to standard models of immigration's effects, where capital is supplied to the market according to a constant and homogeneous elasticity with respect to its rental rate (Borjas, 2013; Dustmann et al., 2013). This elasticity is often framed as equaling zero, reflecting "the short run" when capital is fixed, or approaching infinity, reflecting "the long run" when the rental rate is fixed (Borjas, 2003; Card, 2009).

My intervention is to posit that firms may differ in which of these cases they are closer to—i.e., in the sensitivity of their financing costs to adjustments of their capital stocks. Such differences translate into differences in wages and employment across firms only if labor markets are not perfectly competitive, so I further assume that firms have monopsony power over workers. In a model of monopsonistic labor markets in which more labor makes capital more productive and firms differ in the steepness of their financing-cost curves, I show that the sensitivity of a firm's financing costs has little impact on its hiring of immigrants in response to a market-level immigration shock. However, a higher sensitivity leads to a sharper decline in the firm's capital intensity, depressing labor productivity in a way that decreases wages and, depending on the elasticity of native labor supply, also native employment.

To endogenize why firms may differ in this way, I extend my model to incorporate credit markets, in which firms can borrow from lenders to purchase capital in quantities beyond what they have in net worth. Firms choose their capital stocks prior to realizing a shock to total factor productivity, choose how many workers to employ after realizing the shock, and finally decide whether to pay their lenders or to default and forfeit their profits. In the case of default, lenders observe the realized shock only after paying a verification cost, and this agency problem leads to an external finance premium—that is, a firm's financing cost increases in its leverage (Townsend, 1979; Bernanke et al., 1999). I show that its financing cost is also convex in leverage, such that, below a high threshold value of leverage, initially higher-leverage firms face steeper financing-cost curves. A firm's initial leverage therefore serves as my proxy for the sensitivity of its financing costs to additional borrowing, and my model's predictions about firms' heterogeneous responses to an immigration shock are restated in terms of it.

Descriptives. In the second step of my analysis, I document key stylized facts about Germany during the 2010s, providing descriptive evidence from this setting for the mechanisms in my model. Using a 2% sample of workers' labor market biographies based on administrative social security records, I begin by describing the inflows that raised the immigrant share of employment from 11% in 2010 to 18% in 2019 and explained the majority of total employment growth over this period. These inflows were driven by the interaction of origin-country conditions with various immigration policy changes, including the introduction of freedom of movement for workers from the European Union's newest member states, and asylum reforms that made it easier for individuals from outside the EU to enter Germany and, eventually, its labor market. Regardless of their diverse origins, these recent immigrants tended to be younger than natives and to find lower-wage jobs in less skill-intensive sectors.

I next consider data on German corporations' financial statements, whose disclosure has been legally mandated since 2007, to show that the large immigration shock of the 2010s coincided with a sharp decline in German firms' capital intensity. Exhibiting relative stability from 2007 to 2010, the ratio of net tangible fixed assets to employees fell 13% by 2019 among firms with balanced panels of both measures. The decline was sharper among initially high-leverage firms than among low-leverage ones, a divergence that was driven not by different rates of employment growth but rather by different rates of capital investment. This divergence suggests that large initial debt burdens may have made it difficult for firms to adjust their capital stocks in response to the immigration-induced increase in labor supply.

Finally, as further evidence suggesting the important role of firm leverage, I report three correlations. First, I show that the variation in capital investment across German

firms between 2010 and 2019 was mostly explained by growth in the debt rather than the equity on their balance sheets, demonstrating their dependence on credit markets. Second, using data on firms' interest paid, I find that the average interest rates of initially high-leverage firms increased more than those of low-leverage firms for the same proportional increase in debt, consistent with leverage steepening a firm's financing-cost curve. Lastly, based on a custom link between these financial statements of German enterprises and the social security records of their constituent establishments, I document that, relative to initially lower-leverage firms, higher-leverage ones decreased their capital intensity by more when hiring immigrants.

Identification. To investigate whether this relationship was causal, my third step introduces and validates an ethnic-enclave shift-share instrument to identify the effects of immigration into local labor markets. If newly arriving immigrants prefer to settle in the same locations as earlier immigrants, and the local labor demand shocks that attracted those earlier immigrants are uncorrelated with later such shocks, then each origin country's share of local employment in the past is a valid instrument for local inflows of immigrants today (Card, 2009; Dustmann et al., 2013). I thus construct weighted sums across origin countries of their shares of local employment in 1993, with the shifts reflecting the scale of their immigrants' nationwide inflows into the German labor market from 2010 to 2019.

Arguing that the origin country-specific shares are exogenous conditional on native characteristics in 1993, I implement the validation tests recommended by Goldsmith-Pinkham et al. (2020). Focusing on the effect of immigration on local total employment, I find that heteroskedasticity-robust over-identification tests do not reject. However, some origin countries' shares yield weak just-identified first stages and therefore also biased second-stage estimates, which conventionally constructed shifts fail to sufficiently down-weight in my setting. I show that this issue can be overcome by reweighting each origin country to take greater account of its share's just-identified first-stage power, yielding estimates closer to those yielded by over-identified estimators robust to many weak instruments. Based on this reweighting, I find that a 10-percentage-point increase in immigrant employment relative to initial total employment led to only a 6-percentage-point increase in total employment at the commuting zone level. The implied negative effect on local native employment is consistent with firms incompletely adjusting their capital stocks in response to immigration.

Results. In my fourth and final step, I use this same shift-share instrument to estimate the firm-level effects of immigration into local labor markets, characterizing their heterogeneity with respect to firms' initial leverage. Specifically, I regress changes in firms' outcomes from 2010 to 2019 on changes in local immigrant employment relative

to initial total employment in their respective commuting zones. Still instrumenting immigration with earlier immigrants' settlement patterns and controlling for native characteristics in 1993, I also now account for nationwide shocks specific to particular cells of firms defined by their initial leverage, age, size, and other characteristics. On average, a 10-percentage-point increase in local immigrant employment relative to initial local total employment led to a 7.3% decline in firms' capital intensity, 2.4% decline in their mean wage, and 4.2-percentage-point decline in their native employment relative to their initial total employment. These estimates suggest that the large immigration shock in Germany after 2010 contributed to the sharp decline observed in German firms' capital intensity, leading to losses for their workers.

To test my model's predictions that these effects were shaped by firm heterogeneity in capital-market frictions, I interact both the inflows of immigrants and the shift-share instrument with each firm's tercile in the 2010 leverage distribution. A key first result, which is also consistent with my model, is that leverage did not seem to impair firms' ability to hire immigrants: in response to the same local immigration shock, firms along the initial leverage distribution did not meaningfully differ in their rates of hiring immigrants. This is in contrast to the considerable differences in immigrant hiring between younger and older firms, as well as between smaller and larger firms. Thus, despite any correlation of firms' initial leverage with their other observable characteristics, leverage seems to capture a distinct dimension of firm heterogeneity in responding to an immigration-induced increase in labor supply.

Although firms hired immigrants at similar rates regardless of their initial debt burdens, I find evidence consistent with both my model's predictions and my descriptives that initial leverage made it more difficult for firms to adjust their capital stocks in response to immigration. A 10-percentage-point increase in local immigrant employment relative to initial local total employment led to a 9.1% decrease in the capital intensity of the initially highest-leverage firms, compared to only a 6.0% decrease in that of the lowest-leverage firms. While this comparison is limited by the noisiness of changes in firms' balance sheets when regressed on local immigration, I do detect statistically significant differences in firms' payroll responses to immigration: wages fell by 3.3% (1.7%) at the initially highest-leverage (lowest-leverage) firms, and native employment fell by 7.8 (3.1) percentage points.

Contributions. This paper contributes to three distinct literatures that are rarely brought together. The first is the vast literature in labor economics on the effects of migration-induced labor supply shocks on incumbent workers as well as firms. Most studies have focused on the effects on incumbent wages and employment (Card, 1990; Altonji and Card, 1991; Hunt, 1992; Boustan et al., 2010; Glitz, 2012; Dustmann et al., 2013; Foged

and Peri, 2016; Dustmann et al., 2017; Monras, 2020; Beerli et al., 2021; Borjas and Edo, 2026; Imbert and Ulyssea, 2026). Despite capital adjustment's conceptually important role in such studies, estimates of the effects on firms' capital intensity are sparse, and the few studies providing them have tended to abstract from or find evidence against the importance of capital-market frictions (Lewis, 2011; Mitaritonna et al., 2017; Lafortune et al., 2019; Gorrín, 2020; Imbert et al., 2022). My contribution is therefore to model and document how the financial constraints faced by firms when adjusting their capital stocks shape immigration's effects on their workers. Others have highlighted the related implications of firms' technology choices or entry and exit decisions for workers (Lewis, 2013; Dustmann and Glitz, 2015; Aksu et al., 2022; San, 2023; Mahajan, 2024).

Second, this paper contributes to the literature in financial economics on how financial frictions shape firms' investment decisions. A large empirical literature in corporate finance has debated how to detect such frictions in firms' investment and financing behavior (Fazzari et al., 1988; Kaplan and Zingales, 1997; Almeida et al., 2004; Whited and Wu, 2006; Almeida and Campello, 2007; Denis and Sibilkov, 2010; Lian and Ma, 2021). In macrofinance, the frictions faced by firms as borrowers in credit markets in particular have received considerable attention both theoretically (Myers, 1977; Townsend, 1979; Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997) and empirically (Gertler and Gilchrist, 1994; Giroud and Mueller, 2017; Ottonello and Winberry, 2020; Bahaj et al., 2022; Anderson and Cesa-Bianchi, 2024). These empirical studies have emphasized that differences across firms in the steepness of their financing-cost curves lead to differences in their responsiveness to various kinds of economic shocks. I extend this line of inquiry to the case of immigration-induced labor supply shocks, showing that firms apparently unconstrained in their ability to hire immigrants may nevertheless be constrained in their ability to adjust their capital stocks, and highlighting the implications for their workers.

Finally, this paper relates to the literature at the intersection of labor and finance on the implications of credit supply for labor demand. Exploiting firm-level variation in exposures to different lenders, existing studies have shown that firms facing negative credit supply shocks can experience declines in their borrowing, investment, or productivity that feed through to their employment or wages (Khwaja and Mian, 2008; Chodorow-Reich, 2014; Cingano et al., 2016; Bentolila et al., 2018; Berton et al., 2018; Huber, 2018; Popov and Rocholl, 2018; Greenstone et al., 2020; Lenzu et al., 2026; Moser et al., 2026). Whereas these studies underline the effects of shifts in credit supply on labor demand, I argue that the shape of the credit supply curve faced by each firm helps determine whether an immigration-induced increase in labor supply creates its own labor demand by inducing firms to adjust their capital stocks.

Outline. The rest of this paper is organized as follows. Section 2 develops the model. Section 3 describes the data and presents the descriptive evidence. Section 4 introduces and validates the econometric approach to identifying the effects of local immigration shocks. Section 5 documents the effects of those shocks on firms. Section 6 concludes.

2 Model

This section develops a model of immigration's effects in which firms have monopsony power over workers (Card et al., 2018; Dustmann et al., 2022) and differ in the sensitivity of their financing costs to adjusting their capital stocks. Section 2.1 sets up the model and derives its key predictions, treating as exogenous the heterogeneity across firms in this sensitivity. Section 2.2 endogenizes this heterogeneity through an agency problem between firms that can borrow to finance investment and their lenders (Townsend, 1979; Bernanke et al., 1999), a setup that generates upward-sloping financing-cost curves whose steepness depends on firms' initial leverage. The central prediction of the model is that initial leverage, by determining the sensitivity of a firm's financing costs but not impairing its ability to hire immigrants, shapes how its capital intensity, wages, and native employment respond to a market-level immigration shock.

2.1 Heterogeneous Capital Supply in Monopsonistic Labor Markets

Overview. There are $\bar{L}$ workers in the labor market, comprising $\bar{L}^{nat}$ natives and $\bar{L}^{imm}$ immigrants with identical productivity characteristics and identical distributions of preferences.[2] There is also a fixed number J of firms that use a common production technology combining labor with capital.[3] Firms produce homogeneous output that they sell at a fixed price normalized to one.[4] Workers choose whether and for which firm to work based on their outside options, their idiosyncratic preferences, and the wages offered by firms. Each firm is small relative to the market and internalizes its own upward-sloping labor supply curve: the elasticity of labor supplied to firm j, L_j, with respect to its wage, w_j, is $\beta \in (0, \infty)$, which is homogeneous across firms.

[2] Existing models of immigration's effects in monopsonistic labor markets emphasize potential differences between natives and immigrants in their preferences across firms, labor supply elasticities, or reservation wages (Gyetvay and Keita, 2023; Costas-Fernández and Lodato, 2024; Amior and Manning, 2026; Amior and Stuhler, 2026). However, these models either abstract from firms' choice of capital or assume that capital is supplied to firms at a fixed price. To focus on the implications of capital-market frictions, I abstract from differences between natives and immigrants.

[3] Firm entry and capital stock adjustment are both margins through which the economy can absorb an immigration-induced increase in labor supply (Dustmann and Glitz, 2015; Aksu et al., 2022; Mahajan, 2024). To focus on frictions related to the latter margin, I abstract from the former.

[4] Immigration can also affect output prices (Galaasen et al., 2025; Kim et al., 2026; McCully et al., 2026; Peñaloza-Pacheco, 2026). To focus on adjustment through labor and capital markets, I abstract from this channel and assume a perfectly elastic demand for firms' output, with its price normalized to one.

Firms differ in two dimensions. First, each firm j has its own total factor productivity A_j, an assumption that generates differences in firms' wages and size but not in their responses to a market-level immigration shock. Second, the elasticity of its capital supply, K_j, with respect to its financing cost, ρ_j, is $1/\lambda_j \in (0, \infty)$.[5] This second dimension of firm heterogeneity, which Section 2.2 endogenizes, captures differences in the sensitivity of firms' financing costs to adjusting their capital stocks. As with its labor supply curve, each firm internalizes its own upward-sloping capital supply curve. Heterogeneous λ_j generate firm-specific responses to a market-level immigration shock, in contrast to models of immigration's effects in which firms have monopsony power over workers but are otherwise homogeneous (Dustmann and Schönberg, 2025).

Monopsonistic Labor Markets. Since perfectly competitive labor markets do not accommodate differences across firms in their wages, whether in levels or changes, a model of monopsonistic labor markets is a necessary starting point. I follow Card et al. (2018) and Dustmann et al. (2022) and assume that worker i derives utility u_{ij} not only from the wage w_j that they earn if they choose to work for firm j but also from their idiosyncratic preference ϵ_{ij} for the non-wage amenities that the firm provides. Likewise, they derive utility u_{ib} not only from a fixed benefit w_b that they earn if they choose to not work but also from their idiosyncratic preference for not working. Worker i's preferences across their available choices $\mathcal{J} = \{1, \ldots, J, b\}$ are summarized by:

$$\forall j \in \mathcal{J}: \quad u_{ij} = \beta \ln w_j + \epsilon_{ij}$$

where $\beta \in (0, \infty)$ is the common utility weight on the log pecuniary reward offered by choice $j \in \mathcal{J}$. β governs the sensitivity of each worker's utility to changes in each firm's wage, reflecting the market power that firms have over workers. Just as existing studies of immigration's effects in monopsonistic labor markets abstract from the importance of capital-market frictions to focus on differences between natives and immigrants in their labor supply elasticities (Costas-Fernández and Lodato, 2024; Amior and Stuhler, 2026), I assume that β is homogeneous to focus on capital-market frictions.

Labor Supplied to Firms. If worker i's preferences ϵ_{ij} across choices are independent draws from a common type I extreme value distribution, the arguments from McFadden (1977) imply that the labor supplied to firm j given the vector of pecuniary rewards $\{w_j\}_{j \in \mathcal{J}}$ available to the $\bar{L}$ workers is described by:

$$L_j = \frac{\bar{L}\, w_j^{\beta}}{\sum_{j' \in \mathcal{J}} w_{j'}^{\beta}}$$

[5] As $\lambda_j \to \infty$ for all firms, the model approaches the "short-run" case of a fixed capital stock discussed in Section 1. Likewise, as $\lambda_j \to 0$ for all firms, it approaches the "long-run" case of a fixed financing cost.

If the firm is small enough to ignore the impact of changes in its own wage w_j on the sum $\sum_{j' \in \mathcal{J}} w_{j'}^{\beta}$, then the upward-sloping labor supply curve that it internalizes is:

$$w(L_j) = \left(\frac{\sum_{j' \in \mathcal{J}} w_{j'}^{\beta}}{\bar{L}} \right)^{1/\beta} L_j^{1/\beta} \tag{1}$$

Since β is homogeneous, $w(L_j)$ is a common rather than a firm-specific function of L_j.

Labor Supplied to the Market. The labor supplied to firms sums to the market's supply:

$$L = \sum_{j \in \mathcal{J} \setminus \{b\}} L_j = \frac{\bar{L} \sum_{j \in \mathcal{J} \setminus \{b\}} w_j^{\beta}}{\sum_{j \in \mathcal{J}} w_j^{\beta}}$$

Production Technology. The common technology is Cobb-Douglas in capital and labor, exhibits constant returns to scale, and has $\alpha \in (0, 1)$ as its capital elasticity of output:

$$F(K_j, L_j) = K_j^{\alpha} L_j^{1-\alpha}$$

Firm Heterogeneity. I assume that firms differ in only two dimensions: their total factor productivity and the sensitivity of their financing costs to adjusting their capital stocks. First, firm j's production function depends on its own total factor productivity A_j, which simply rescales the output Y_j generated using the common production technology:

$$Y_j = A_j F(K_j, L_j) = A_j K_j^{\alpha} L_j^{1-\alpha} \tag{2}$$

Second, capital K_j is supplied to firm j based on an exogenous firm-specific elasticity $1/\lambda_j \in (0, \infty)$ with respect to a firm-specific financing cost ρ_j:

$$\frac{d \ln K_j}{d \ln \rho_j} = \frac{1}{\lambda_j}$$

As with labor supply, the firm internalizes its upward-sloping capital supply curve:

$$\rho_j(K_j) = \underline{\rho}_j K_j^{\lambda_j} \tag{3}$$

where $\underline{\rho}_j$ is a fixed firm-specific scale parameter. This setup implies that capital is in unlimited supply to the economy as a whole: each firm's financing cost depends only on its own capital stock, not on how much capital other firms use. However, firms face different frictions in obtaining it: those with small λ_j can acquire it at a nearly fixed price, while those with large λ_j face sharp increases in their financing costs.

Profit Maximization. Firm j chooses capital K_j and labor L_j to maximize profits given its production $A_j F(K_j, L_j)$, financing-cost curve $\rho_j(K_j)$, and labor-cost curve $w(L_j)$:

$$\max_{K_j, L_j} \left\{ A_j F(K_j, L_j) - \rho_j(K_j) K_j - w(L_j) L_j \right\} \tag{4}$$

Equation (4) illustrates the key deviation of this model from standard models of the labor market effects of immigration (Dustmann and Schönberg, 2025): firms differ in their financing-cost curves $\rho_j(K_j)$ and internalize these differences. This creates scope for firm-specific responses to a market-level immigration shock that are attributable to capital-market frictions, namely, to the heterogeneous steepness λ_j of those curves.

Equilibrium. In equilibrium, the first-order conditions of Equation (4) with respect to K_j and L_j are satisfied for all firms, and the labor market clears. The clearing of the capital market is guaranteed by the firm-specific capital supply curves.

Firm-Specific Responses to a Market-Level Immigration Shock. Consider an exogenous shift $dI \equiv d\bar{L}^{imm} / \bar{L}_0$ in the number of immigrant workers in the labor market relative to the initial number of workers $\bar{L}_0$, where the subscript 0 denotes the initial equilibrium value. In Appendix A.1, given Equations (1)–(4), I derive the following proposition, which characterizes how the heterogeneity across firms in the capital-market frictions that they face shapes their responses to this market-level immigration shock:

Proposition 1 *(a) If the labor market's initial share of immigrants is low (i.e., $\bar{L}_0^{imm} / \bar{L}_0 \approx 0$), then the rate at which a firm j hires newly arriving immigrants relative to its initial total employment is approximately equal across firms facing different financing-cost curves $\rho_j(K_j)$. (b) However, firms whose curves are steeper (i.e., with higher λ_j) experience more negative proportional changes in their capital-labor ratios K_j / L_j, wages w_j, and native employment L_j^{nat}.*

The intuition for part (a) of Proposition 1 is that newly arriving immigrants sort into firms in proportion to the firms' respective shares (i.e., $L_{j0} / \bar{L}_0$ for firm j) of the initial number of workers $\bar{L}_0$. Since higher-productivity firms (i.e., with higher A_j for a given combination of ρ_j and λ_j) pay higher wages and employ more workers in the initial equilibrium (see Appendix A.1), they also attract larger numbers of newly arriving immigrants in the new equilibrium in proportions similar to before. A low initial share of immigrants in the labor market ensures that any reallocation of earlier immigrants is small relative to the proportional distribution of inflows. Thus, firm heterogeneity in capital supply does not lead firms to differ much in their rates of hiring immigrants.

Nevertheless, these differences in the sensitivity of firms' financing costs to adjusting their capital stocks do lead to heterogeneous responses in their capital intensity, wages,

and native employment to a market-level immigration shock. The intuition for part (b) of Proposition 1 is that, the more sharply a firm's financing cost rises due to an increase in capital demand, the more this higher cost crowds out the firm's incentive to expand its capital stock in response to an immigration-induced increase in the marginal productivity of capital at the firm (see Appendix A.1). The firm's capital stock therefore fails to keep up with its growing employment, leading to a decline in its capital intensity. This decline also decreases the marginal productivity of labor at the firm, resulting in falling wages that induce its native workers to either exit the labor market or switch to other firms that may offer more attractive wages in the new equilibrium.

2.2 Credit-Market Frictions and the Role of Firm Leverage

Credit Markets. So far, I have treated the sensitivity of firms' financing costs as exogenous. I now begin endogenizing this key dimension of firm heterogeneity by introducing a credit market, in which firms can borrow from lenders to finance investments in their capital stocks. My extended model adapts the partial-equilibrium setup from Bernanke et al. (1999) to analyze how the credit-market frictions faced by firms shape immigration's effects in monopsonistic labor markets. Rather than rent capital by paying a rental rate, firms now purchase it at a fixed price normalized to one.[6] They can finance these purchases from two distinct sources: their own net worth N_j, which they have accumulated for exogenous reasons based on their past activities, and loans D_j that they can obtain from a unit mass of homogeneous lenders. These lenders themselves have access to a perfectly elastic supply of funds: they can obtain an unlimited quantity at a fixed wholesale interest rate $\underline{r}$, which is analogous to the "long-run" cases discussed in Sections 1 and 2.1 with unlimited capital supplied to the economy as a whole.

Frictions. In this setup, I consider how firms and their lenders together face an agency problem, whose timing is as follows. Before deciding how much capital K_j to purchase, and therefore also how much $D_j = K_j - N_j$ to borrow from lenders at the interest rate r_j, firm j faces uncertainty about a shock ω_j to its own total factor productivity A_j. It then observes ω_j before choosing how many workers L_j to employ, taking both ω_j and K_j as given. Finally, after paying its workers their wages at the rate $w(L_j)$, the firm decides whether to pay its lenders or to default and forfeit its net-of-wages profits $\omega_j A_j F(K_j, L_j) - w(L_j)L_j$ to them. In the case of default, lenders observe the realized shock ω_j only after paying a fixed fraction μ of the net-of-wages profits.[7]

[6] The financing cost referred to in Section 2.1 was implicitly a rental rate. To focus on frictions that firms face in financing investment, rather than those that they face in physically adjusting their capital stocks (Cooper and Haltiwanger, 2006) or as buyers of investment goods (Bertolotti et al., 2027), I assume a perfectly elastic supply of firms' capital inputs and normalize its price to one.

[7] This timing assumes that lenders cannot infer ω_j from firm j's employment or wages, both of which

In Appendix A.2, extending the proofs from Bernanke et al. (1999) to a setting with monopsonistic labor markets, I show how this problem gives rise to a well-established result regarding the financing-cost curve that a firm faces when choosing its capital stock: its financing cost is increasing in its chosen debt, D_j, holding fixed its net worth, N_j. Intuitively, a firm that borrows more relative to its net worth owes more to its lenders and therefore owns less equity in its net-of-wages profits. This makes it more willing to default when it draws a low ω_j, and lenders demand compensation for the higher verification costs associated with this higher default rate in the form of an external finance premium. The resulting upward-sloping curve provides a microfoundation for the firm-specific financing-cost curve $\rho_j(K_j)$ discussed in Section 2.1.

Role of Firm Leverage. For analyzing firm-specific responses to a market-level immigration shock, the relevant feature of this financing-cost curve is not its monotonicity but rather its steepness at the level of a firm's capital stock in the initial equilibrium. Whereas Bernanke et al. (1999) highlight the former property, I follow others (Giroud and Mueller, 2017; Ottonello and Winberry, 2020; Bahaj et al., 2022; Anderson and Cesa-Bianchi, 2024) in interpreting the latter as an index of the firm's financial constraints. In Appendix A.2, I also derive the following proposition, which characterizes the important role of firms' initial leverage in determining the sensitivity of their financing costs to adjusting their capital stocks and, thereby, in determining immigration's effects:

Proposition 2 *(a) Under certain regularity conditions, and holding its net worth fixed, a firm's log financing cost is convex in its log leverage below a threshold. (b) This implies that, below a threshold level of leverage, firms with higher initial leverage are at steeper points in their financing-cost curves $\rho_j(K_j)$ (i.e., λ_j is not a constant but increasing in D_{j0}/K_{j0}). (c) If the labor market's initial share of immigrants is low (i.e., $\bar{L}_0^{imm}/\bar{L}_0 \approx 0$), firm heterogeneity in initial leverage does not lead to firms differing much in their rates of hiring newly arriving immigrants. (d) However, initially higher-leverage firms (i.e., with higher λ_j) experience more negative proportional changes in their capital-labor ratios K_j/L_j, wages w_j, and native employment L_j^{nat}.*

The intuition for part (a) of Proposition 2 is that, if a firm's leverage is initially low, then more borrowing does not change its probability of default by much. In contrast, a further increase in borrowing for a firm that is already highly indebted raises its probability of default sharply. The greater sensitivity of this probability to additional leverage translates to a greater sensitivity of the firm's financing cost, as lenders demand compensation for the verification costs that they increasingly expect to incur. Part (b) then follows from part (a), with the threshold conditions discussed in Appendix A.2.

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depend on it. For instance, such inference would require lenders to audit the firm's books, which is itself costly; the verification cost μ can be interpreted as including such auditing.

Finally, parts (c) and (d) of Proposition 2 simply combine part (b) with Proposition 1. In response to an immigration-induced increase in labor supply, initially higher-leverage firms are not impaired in their ability to hire immigrants. However, since they face steeper financing-cost curves, they do not adjust their capital stocks by as much, so their capital intensity, wages, and native employment fall by more than for initially lower-leverage firms.[8] The remainder of this paper tests these predictions empirically.

3 Data and Descriptives

This section describes the data that I use to investigate the setting of Germany during the 2010s and documents key stylized facts related to the predictions of the model developed in Section 2. Section 3.1 introduces the different datasets containing information on German workers and firms. Section 3.2 characterizes the immigration shock that the German economy absorbed. Section 3.3 documents the coinciding decline in German firms' capital intensity. Section 3.4 presents descriptive evidence that firm leverage shaped the relationship between immigration and the decline in capital intensity.

3.1 Data

My empirical analysis is based on four distinct datasets: workers' social security records; corporations' financial statements; national accounts data on economy-wide stocks of fixed assets and price levels; and a custom link between enterprise-level financial statements and establishment-level social security records. I next briefly describe each dataset, elaborating on my data-cleaning steps related to each in Appendix B.

Workers' Labor Market Biographies. My first dataset is the Sample of Integrated Labour Market Biographies, made available by the German Federal Employment Agency's Institute for Employment Research (Graf et al., 2025). The data contains a 2% sample of workers' labor market biographies based on administrative records from Germany's social security system, including employer notifications about the employment and individual characteristics of their workers (Schmucker and Berge, 2025).[9] Complete for reunified Germany since 1993, this data has been widely used in labor economics due both to its worker-level granularity and to its accuracy, as employers face penalties for misreporting information about their workers (Dustmann et al., 2009; Gathmann and Schönberg, 2010; Glitz, 2012). For my purposes, the key variable that it contains is the nationality of each worker as of each of their spells, which allows me to identify

[8] This model of credit-market frictions allows for heterogeneity across firms in both their total factor productivity A_j and their net worth N_j. Differences across firms in their initial leverage would therefore have to arise from differences in these exogenous parameters.

[9] Since civil servants and self-employed workers are not covered by the social security system, they do not appear in this data. This omission matters little for my analysis, which focuses on private enterprises.

immigrants as those workers ever observed with non-German nationality, and their origin countries as the non-German nationality with which they are most frequently observed.[10] Since the data also contains information on each worker's employment status, wage, age, education, and gender as well as their employer's industry and county, I can construct the regional immigration shocks and controls for native characteristics that I exploit to identify the effects of immigration in Sections 4 and 5.

Corporations' Financial Statements. The second dataset contains information on German corporations' financial statements, accessed via Moody's DataHub. The data's existence owes to regulatory changes in Germany that, starting in 2007, required all German corporations to submit electronic filings of their balance sheets and larger corporations to also provide income statements and other financials. These filings are then collected and distributed by Moody's, whose subsidiary Bureau van Dijk's Orbis data product has been widely used in corporate finance and firm dynamics to study the behavior of private corporations (Gopinath et al., 2017; Nikolov et al., 2021; Kalemli-Özcan et al., 2024).[11] In corporations' balance sheets, the key variables that I observe are their net tangible fixed assets (i.e., their capital stock net of accumulated depreciation), their total assets, and their long-term debt.[12] In their income statements and other financials, I also observe their interest paid and their number of employees. Together, these variables allow me to analyze firms' capital intensity, leverage, and borrowing costs.

National Accounts Data. Both to validate the micro-data on corporations' tangible fixed assets and to identify relevant price deflators, I consider a third dataset on corporations' aggregate stocks of fixed assets from Germany's national accounts, accessed via the German Federal Statistical Office's GENESIS-Online database. The data contains information on the aggregate tangible fixed assets of German corporations in both nominal and real units—that is, at current replacement cost as well as based on a price-adjusted chain index. The latter provides an official measure of corporations' real aggregate tangible fixed assets, while comparing the two series allows me to construct an index by which I can deflate their individual tangible fixed assets.[13] I similarly deflate all

[10] This definition ensures that non-Germans who eventually naturalize as German citizens continue to be classified as immigrants. However, it risks misclassifying as immigrants those born in Germany to non-German parents before the introduction of conditional birthright citizenship in 2000.

[11] Each vintage of Orbis provides data on only a subset of the years in which each corporation has been active, so complete coverage requires linking historical vintages (Kalemli-Özcan et al., 2024). Moody's DataHub overcomes this problem, providing data on all of the years available for each corporation.

[12] I focus on corporations' long-term debt because, as Section 3.4 shows, it is what drives their capital investment, and because data coverage of short-term debt is more limited.

[13] Germany's national accounts data on stocks of fixed assets is limited in two respects. First, it does not provide data on corporations' tangible fixed assets at historical cost, which is the convention used on their balance sheets; this makes the price deflator constructed by comparing the current replacement cost series to the price-adjusted chain index a necessary but imperfect substitute, in contrast to the aggregate

other nominal variables, including workers' wages and corporations' other assets and liabilities, by Germany's consumer price index.

Custom Link between Enterprise-Level Financials and Establishment-Level Payrolls. My final dataset is a custom link between the enterprise-level financial statements obtained from Moody's DataHub and establishment-level social security records that I further obtain from the Institute for Employment Research (IAB). The latter, drawn from the IAB's Establishment History Panel (Ganzer et al., 2025a, 2025b), contain information on the total employment and mean wages of different categories of workers employed at each establishment, including natives and immigrants.[14] Linking this payroll information to the data on financial statements, I can analyze how a firm's capital intensity changes when it hires immigrants. The link exploits a mapping, built by researchers at the IAB and the Zentrum für Europäische Wirtschaftsforschung, between establishment identifiers from Germany's social security system and enterprise identifiers from Bureau van Dijk.[15] While mine is a custom dataset, other studies have used similar links to explore related questions at the intersection of labor and financial economics (Brinkmann et al., 2025; Brinkmann and Wolter, 2026; Liang, 2026; Moser et al., 2026).

3.2 Immigration to Germany during the 2010s

Using data on workers' social security records, I first characterize the inflows of immigrants into the German labor market. Figure 1a plots the evolution of the immigrant share of employment from 2007 to 2019. Starting in 2011, this immigrant share rose by at least 0.4 percentage points and as much as 1.1 percentage points in every year, growing from 11.3% in 2010 to 18.5% in 2019.[16] Figure 1b shows that this sharp rise in the immigrant share was driven by immigrant employment growing by almost 90% relative to 2010. This compares to only 7% growth in the employment of natives, as their shrinking working-age population partially offset the employment gains from their declining unemployment rate (Kosyakova, 2025). Most of the 16% growth in total employment over this period was therefore explained by inflows of immigrants.

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measures at historical cost that are available for the United States (Desazars, 2026). Second, official stocks of tangible fixed assets by industry are reported only for broader or narrower asset categories than tangible fixed assets, which is the variable that I observe in the micro-data; I therefore use a single deflator for the corporate sector as a whole, which importantly excludes households and the government.

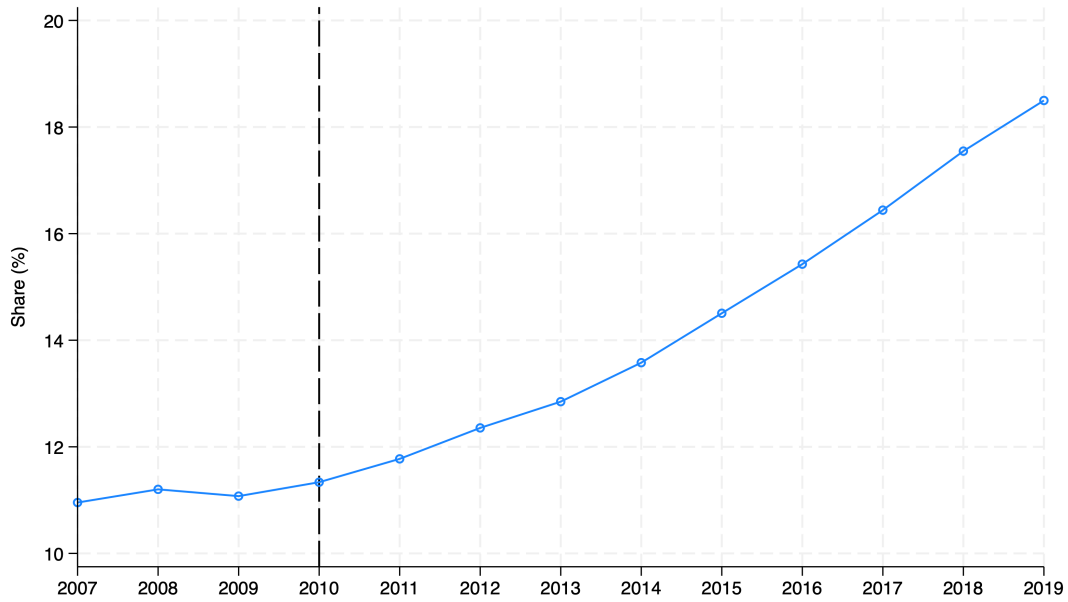
[14] In this establishment-level data, in which workers' histories are not observed, immigrants necessarily refer only to those with non-German nationality as of the spells when an establishment employed them.

[15] This mapping is based on a procedure that matches names and addresses across enterprises and their associated establishments (Doherr, 2023; Diegmann et al., 2024; Gottschalk et al., 2025).

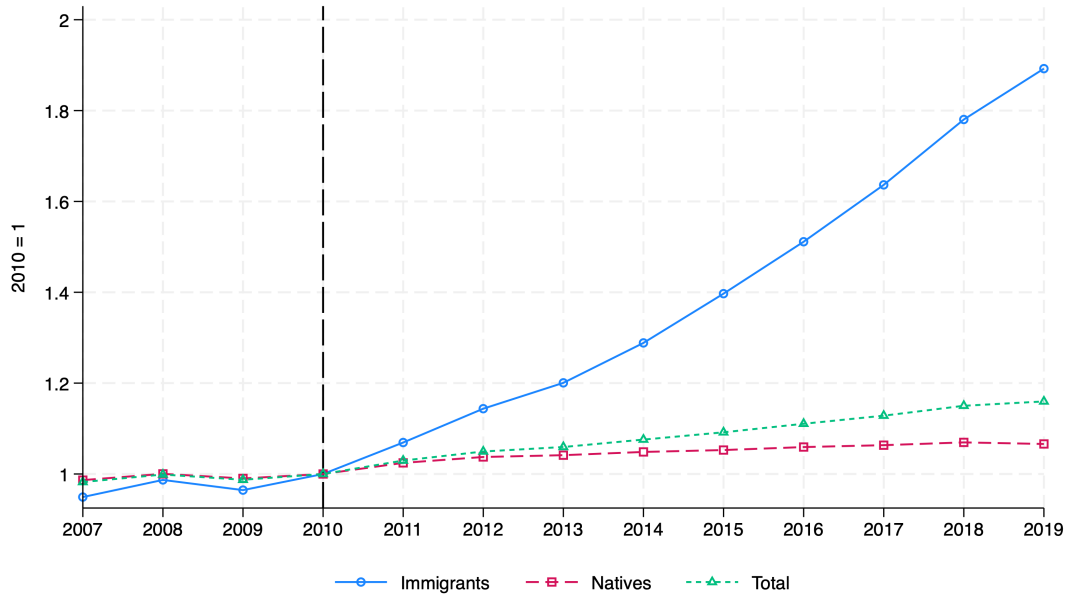
[16] In Figure 1, employment is measured in full-time equivalent units, with part-time and marginal workers assigned weights of 0.5 and 0.2, respectively. Appendix Figure C1 shows that the immigrant share of the number of employees evolved similarly, so these weights do not change the shock's scale.

Figure 1: Immigration to Germany

(a) Immigrant Share of Employment



(b) Immigrant, Native, and Total Employment Relative to 2010



Sources: Sample of Integrated Labour Market Biographies.
Notes: This figure describes the inflows of immigrants into the German labor market from 2007 to 2019. Panel (a) plots the immigrant share of employment. Panel (b) plots the levels of immigrant, native, and total employment in each year relative to 2010. The sample includes workers of ages 15–64 in full-time, part-time, or marginal employment on June 30 of each year. Employment is measured in full-time equivalent units, with part-time and marginal workers assigned weights of 0.5 and 0.2, respectively.

This large decadal immigration shock was the result of various changes to Germany's immigration policy interacting with and even responding to push factors in immigrants' origin countries. The first was the 2011 introduction of freedom of movement to workers from eight Eastern European countries (Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, and Slovenia) that had joined the European Union in 2004. Workers from Bulgaria and Romania, which had joined the EU in 2007, gained the same freedom in 2014, as did those from Croatia, which joined in 2013, in 2015. Coinciding with economic weakness in many of these origin countries, each of these reforms led to the start of sharp inflows of EU migrants into Germany (Bertoli et al., 2016).

The arrivals of non-EU migrants were then triggered by two additional reforms in 2015–2016, introduced in response to the global refugee crisis that was particularly acute in Syria, Iraq, and Afghanistan. To make room in its otherwise overwhelmed asylum system, Germany created new legal pathways for workers from six Western Balkan countries (Albania, Bosnia and Herzegovina, Kosovo, Montenegro, North Macedonia, and Serbia) to enter the German labor market with minimal requirements. At the same time, the pressure on the Dublin Regulation (i.e., the rule that the EU member state that a person first entered was responsible for processing their asylum application) and its eventual suspension permitted the arrival of over 1 million refugees in 2015 and 2016 (Bither and Ziebarth, 2018). By the end of the decade, after an initial period when they were not allowed to work, these refugees began entering the labor market.

Appendix Table C1 summarizes the composition of recent immigrants in Germany in 2019 by the respective reform that affected their origin country. Despite their disparate origins, recent immigrants from all the countries affected by Germany's immigration reforms concentrated at the bottom of the wage distribution relative to natives (Appendix Figure C2); origin country heterogeneity is therefore not a focus of this paper. Recent immigrants' concentration in low-wage jobs is consistent with them being younger and more likely to be employed in low-wage sectors like accommodation and food services (Appendix Table C2). However, their university-educated share in 2019 was actually higher than that of natives in 2010, suggesting that downgrading may have made this immigration shock look more like a low-skilled one than conventional education-based understandings of skill would imply (Lewis, 2011; Dustmann et al., 2013).

3.3 German Firms' Declining Capital Intensity

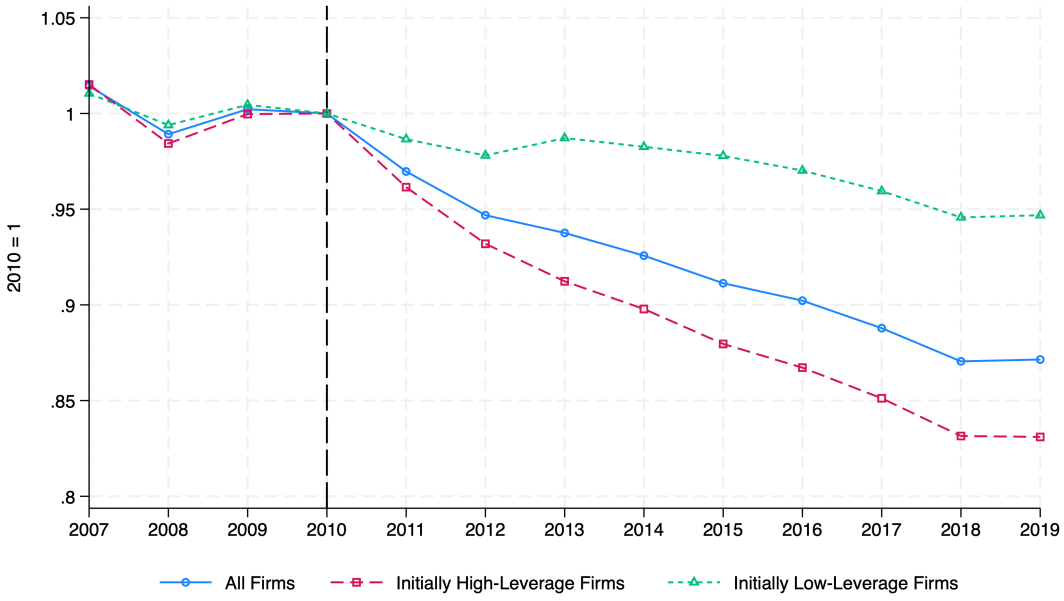
Using data on corporations' financial statements, I next describe the evolution of German firms' capital intensity over the same period from 2007 to 2019. I measure capital intensity as the ratio of their net tangible fixed assets to their number of employees as stated in their balance sheets and other financials, focusing on the firms for which

both variables are available in all years. This focus not only allows me to visualize time trends holding the composition of firms fixed but is also consistent with the aims of the model developed in Section 2—that is, to analyze how firms' intensive-margin investment responses to immigration are shaped by their initial characteristics, in contrast to possible extensive-margin adjustments (Mahajan, 2024; Imbert and Ulyssea, 2026).

The first line in Figure 2a plots the evolution relative to 2010 of the aggregate net tangible fixed assets per employee across all firms.[17] Relatively stable from 2007 to 2010, the ratio began to fall in 2011 and continued falling until 2018, reaching a level 12.9% below its 2010 level. The remaining two lines in Figure 2a separate firms into two groups based on whether their initial leverage (i.e., their mean ratio of long-term debt to total assets from 2007 to 2010) was above or below the median, revealing a striking pattern: relative to 2010, initially high-leverage firms' capital intensity fell 16.9% by 2019, compared to only 5.3% for initially low-leverage firms. Figures 2b and 2c show that this divergent pattern was driven primarily by a divergence in their accumulation of capital rather than in their expansion of headcount, as the net tangible fixed assets of initially high-leverage firms did not keep pace with their growing number of employees.

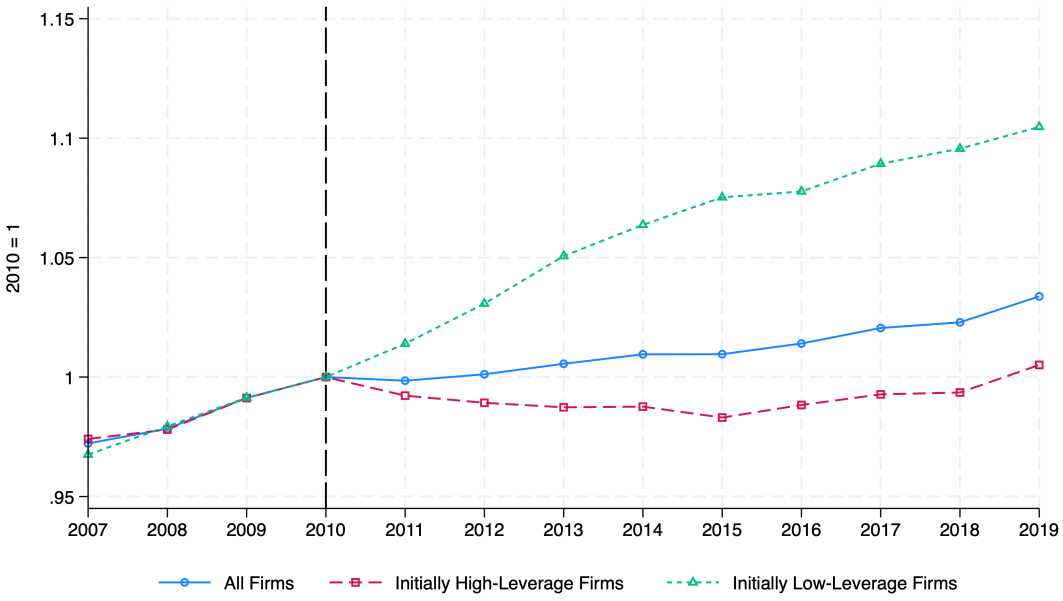
Figure 2: German Firms' Capital Intensity Relative to 2010

(a) Net Tangible Fixed Assets per Employee

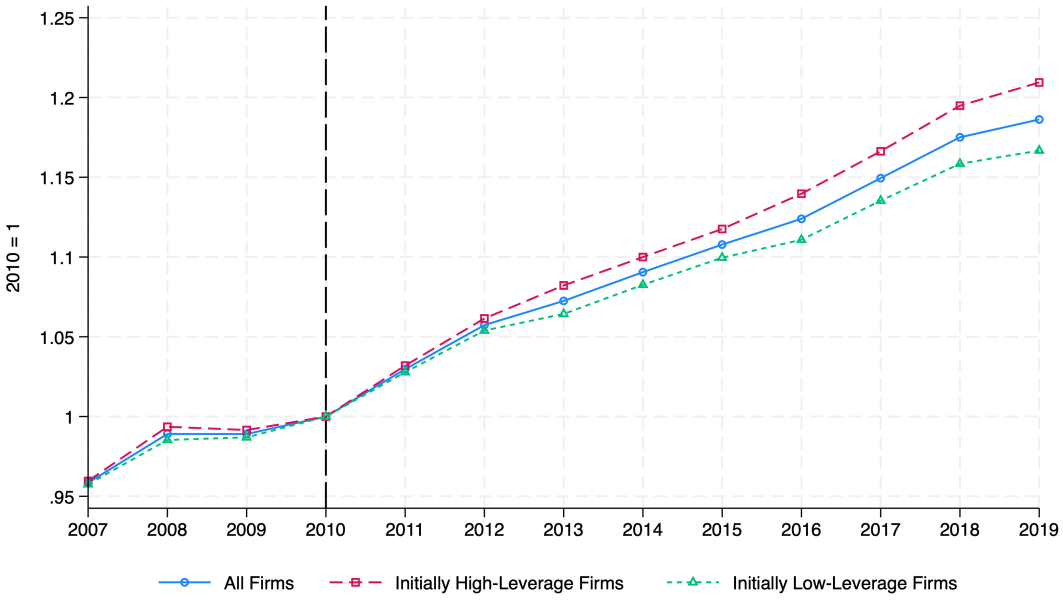


[17] Since, in the aggregate, each firm is implicitly weighted by its number of employees, Figure 2 excludes the top 1% of firms in terms of maximum size (which account for 20% of the total number of employees in 2010) to ensure that the plotted dynamics are not driven only by the very largest firms. Reassuringly, Appendix Figure C3 includes these firms and shows nearly identical patterns.

(b) Net Tangible Fixed Assets



(c) Number of Employees



Sources: Moody's DataHub.
Notes: This figure describes the evolution of German firms' capital intensity from 2007 to 2019, both their aggregate dynamics (i.e., of the total net tangible fixed assets per employee across all firms) and the differences between initially high- and low-leverage firms. Panel (a) plots firms' net tangible fixed assets per employee relative to 2010. Panel (b) plots their net tangible fixed assets relative to 2010. Panel (c) plots their number of employees relative to 2010. Firms are included only if both the numerator and denominator of the ratio are available in all years. The top 1% of firms in terms of maximum size (i.e., number of employees) are excluded. The last two lines separate firms into two groups based on whether their mean ratio of long-term debt to total assets from 2007 to 2010 was above or below the median.

Thus, the immigration shock that the German economy absorbed during the 2010s (see Section 3.2) coincided with a sharp decline in German firms' capital intensity. I corroborate the robustness of the findings in Figure 2 along four dimensions. First, the decline is also observable in Germany's national accounts data on corporations' net tangible fixed assets (Appendix Figure C4).[18] Second, the divergence in capital intensity by firm leverage still holds even if I separate firms into initially high- and low-leverage groups only within other dimensions of firm heterogeneity, including by manufacturing or non-manufacturing firms (Appendix Figures C6a and C6b), by old or young firms (Appendix Figures C6c and C6d), and by large or small firms (Appendix Figures C6e and C6f). Third, the borrowing behavior of initially high- and low-leverage firms also diverged starting in 2011, with only the latter raising new debt at the same time as they expanded their capital stocks (Appendix Figure C7).[19] Finally, both the overall decline in capital intensity and its divergence by firm leverage survive an evaluation of survivorship bias: including all firms with complete data from 2007 to 2010 (rather than from 2007 to 2019), interpolating their net tangible fixed assets and number of employees until their last observations, and allowing firms to drop out thereafter does not change the dynamics plotted in Figure 2 (Appendix Figure C8).

3.4 Descriptive Evidence on the Role of Firm Leverage

As documented in Section 3.3, the decline in German firms' capital intensity during the 2010s was especially sharp among initially high-leverage firms. I now provide further descriptive evidence suggesting that high initial leverage may have impaired a firm's ability to adjust its capital stock in response to the concurrent immigration-induced increase in labor supply, in ways consistent with the model developed in Section 2.

German Firms' Dependence on Debt. For a firm's initial leverage to be a factor shaping its investment response to immigration, credit markets must first and foremost be an important source of financing for it. My first step in establishing the role of firm

[18] Unlike for stocks of fixed assets, the national accounts do not provide information on the total number of employees in the corporate sector as a whole. Appendix Figure C4 therefore compares the growth in corporations' capital stocks according to the national accounts to the growth in the total number of employees according to workers' social security records (see Figure 1b), which are likely to have complete coverage of corporations' employees. Although, by this measure, the decline in firms' capital intensity appears to begin in 2009, Appendix Figure C5 confirms that, in an accounting sense, its continued decline thereafter was attributable to the sharp increase in the number of immigrant employees after 2010.

[19] The relative stability of firms' capital intensity and borrowing behavior from 2007 to 2010, as well as the fact that these pretrends do not appear to differ much by firm leverage, may seem at odds with this pre-period coinciding with the global financial crisis. Indeed, credit spreads for German corporate bonds spiked during the peak of the crisis from 2008 to 2009, at the same time as certain German banks cut lending. However, German credit-market conditions mostly normalized by 2010, before the 2011 onset of the immigration shock. Moreover, the subsequent sovereign debt crisis in the Eurozone during the early 2010s left Germany relatively unscathed (Gilchrist and Mojon, 2018; Huber, 2018).

leverage is therefore to identify which sources of financing drive the variation in capital investment across firms. As alternatives to borrowing, a firm could instead sell more shares to new or existing owners, use internal funds by accumulating new profits or depleting existing cash, and issue other new liabilities or sell other existing assets.

The following accounting identity, derived from the equality of assets with liabilities plus shareholders' equity, exactly decomposes the change dK_j in the net tangible fixed assets on firm j's balance sheet over some horizon:

$$dK_j = dD_j + dE_j + dF_j + dO_j$$

where dD_j is the change in its long-term debt, dE_j is the change in its paid-in equity, dF_j is the change in its internal funds (i.e., the change in its retained earnings minus the change in its cash on hand), and dO_j is the change in its other net liabilities (i.e., the change in its other liabilities minus the change in its other assets).

The following regressions, which normalize each component by the firm's initial total assets A_j, represent a variance decomposition of capital investment across firms:

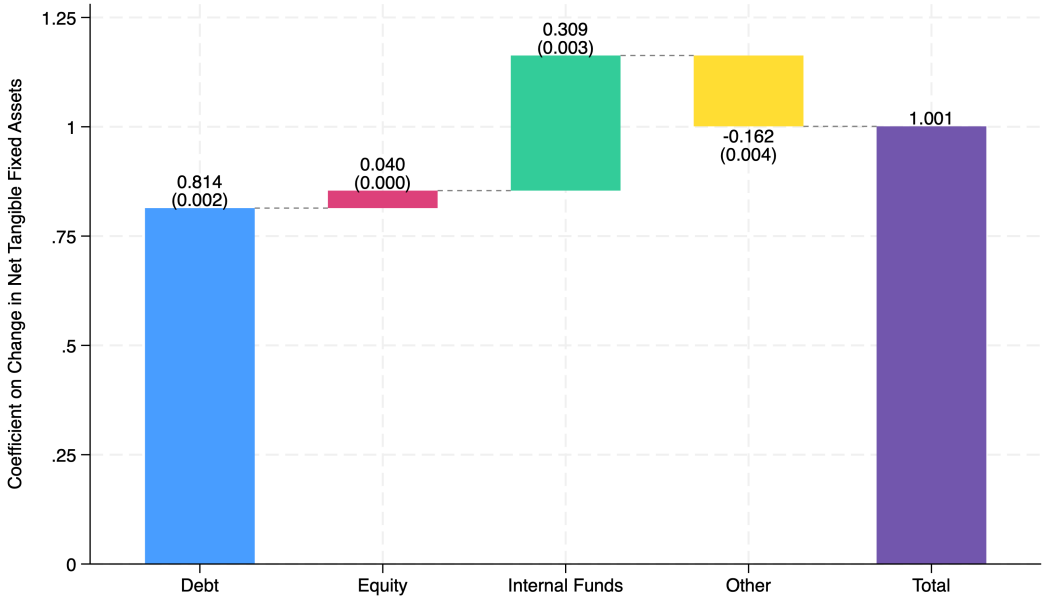
$$\forall Y \in \{D, E, F, O\}: \quad \frac{dY_j}{A_j} = \alpha_Y + \beta_Y \frac{dK_j}{A_j} + u_j \tag{5}$$

where $\beta_D + \beta_E + \beta_F + \beta_O = 1$ due to the accounting identity. Using information from corporations' balance sheets, I estimate Equation (5) on the 145,540 German firms for which $dK_j > 0$ from 2010 to 2019 and I observe all four of its components, since my question is how firms finance expansions, not contractions, of their capital stocks.

Figure 3 visualizes this variance decomposition. Borrowing dD_j accounted for 81.4% of the variation in capital investment across firms. The change in internal funds dF_j was the second most important component, explaining 30.9%, while the change in paid-in equity dE_j contributed little and the change in other net liabilities dO_j entered negatively; the negative sign of the latter's coefficient implies that firms tended to also accumulate other assets when investing. This hierarchy across the different sources of financing is robust to a 1% winsorization (Appendix Figure C9a) and to further weighting each firm by its 2010 total assets (Appendix Figure C9b).

In summary, Figure 3 shows that German firms tended to turn to credit markets to finance expansions of their capital stocks, as changes in debt were the most important driver of the variation in their capital investment from 2010 to 2019. As a result, any impairment of their ability to borrow—such as a steeper financing-cost curve due to their existing debt burdens—may have limited their ability to invest.

Figure 3: Variance Decomposition of Capital Investment across Firms



Sources: Moody's DataHub.
Notes: This figure reports the variance decomposition of the change in net tangible fixed assets from 2010 to 2019 relative to total assets in 2010 across German firms, based on Equation (5) and restricting to firms whose net tangible fixed assets grew over this period. Each bar reflects the estimate from regressing its associated component on the change in net tangible fixed assets. Debt refers to the change in long-term debt relative to initial total assets. Equity refers to the change in paid-in equity relative to initial total assets. Internal funds refers to the change in retained earnings minus the change in cash on hand relative to initial total assets. Other refers to the change in other liabilities minus the change in other assets relative to initial total assets.

Initial Leverage and the Steepness of Credit Supply. Do initially higher-leverage firms face steeper financing-cost curves, as predicted by part (a) of Proposition 2 in Section 2? I attempt to answer this question by combining data on interest paid from corporations' income statements with data on their long-term debt and total assets from their balance sheets. The average interest rate paid by firm j in year t can be calculated as:

$$r_{j,t} = \frac{I_{j,t}}{D_{j,t-1}}$$

where $I_{j,t}$ is its interest paid during year t, and $D_{j,t-1}$ is its debt as of the previous year $t-1$.[20] Although this average interest rate is not a marginal one, Appendix Figure C10 shows that the average interest rate across all firms declined alongside the 10-year German government bond yield, albeit with a lag consistent with the gradual repricing of existing debt; firms' average interest rates therefore still contain useful information about the marginal rates on their new loans.

[20] The timing assumption underlying this definition is that any new debt taken on by firm j during year t accrued no interest until the next year.

For the 5,821 firms for which I can construct this average interest rate in both 2010 and 2019, I consider the following regression specification:

$$d \ln r_j = \alpha + \beta \, d \ln D_j + \gamma H_{j0} + \delta H_{j0} \, d \ln D_j + u_j \tag{6}$$

where $d \ln r_j$ is the change in firm j's log average interest rate from 2010 to 2019, $d \ln D_j$ is the change in its log long-term debt, and H_{j0} is a dummy variable for whether it ranked in the upper half of the distribution of leverage across firms in 2010.

Equation (6) regresses price changes on quantity changes, so the coefficient β combines the effects of different shocks. Whereas credit demand shocks move prices and quantities in the same direction along an upward-sloping credit supply curve, credit supply shocks move prices and quantities in different directions along a downward-sloping credit demand curve. As a result, β cannot be interpreted as a credit supply elasticity.

The parameter of interest, however, is the coefficient δ on the interaction term $H_{j0} \, d \ln D_j$. If $\delta > 0$, initially high-leverage firms saw greater proportional increases in their average interest rates than initially low-leverage firms for the same proportional increase in debt. Formally, δ identifies a lower bound on the difference between the slopes of initially high- and low-leverage firms' credit supply curves under the following condition:

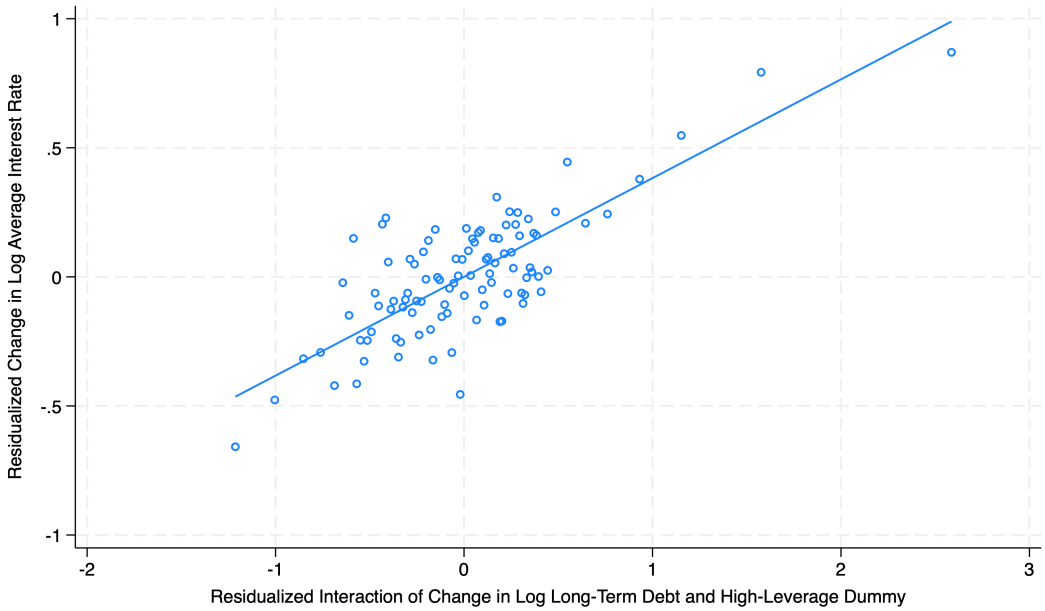
$$Cov[u_j, \widetilde{H_{j0} \, d \ln D_j}] \leq 0$$

where $\widetilde{H_{j0} \, d \ln D_j}$ is the residual from a regression of the interaction term on $d \ln D_j$ and H_{j0}. Intuitively, if credit supply shocks drive at least as much of the variation in $d \ln D_j$ for initially high-leverage firms as they do for low-leverage ones, then the OLS estimate of δ understates how much high initial leverage steepens the credit supply curve. This assumption is supported by evidence that initially higher-leverage firms' investment behavior is more sensitive to credit supply shocks (Kalemli-Özcan et al., 2022).

Figure 4 visualizes how δ is estimated. The vertical axis plots bins of the residualized change in log interest rates $\widetilde{d \ln r_j}$, while the horizontal axis plots bins of the residualized interaction term $\widetilde{H_{j0} \, d \ln D_j}$. The slope is 0.4 and precisely estimated, a positive relationship that also holds within other dimensions of firm heterogeneity like sector and age (Appendix Table C3). Moreover, no strong gradient of interest rate sensitivity to additional borrowing exists along these other dimensions (Appendix Table C4).

Thus, the borrowing costs of initially higher-leverage German firms were more sensitive to additional debt than those of initially lower-leverage ones. This finding is consistent with parts (a) and (b) of Proposition 2 from Section 2.2 and suggests that higher initial leverage may have made it more difficult for firms to finance capital stock adjustments.

Figure 4: Greater Sensitivity of Initially Higher-Leverage Firms' Borrowing Costs



Sources: Moody's DataHub.
Notes: This figure visualizes how the coefficient δ in Equation (6) is estimated, plotting bins of the change in log interest rates $d \ln r_j$ residualized with respect to both the change in log debt $d \ln D_j$ and the initially high-leverage dummy H_{j0} against bins of the residualized interaction term $H_{j0}\, d \ln D_j$. The 100 bins are constructed after a 1% winsorization. A firm's average interest rate is the ratio of its interest paid during a year to its long-term debt as of the previous year. The initially high-leverage dummy indicates whether the firm ranked in the upper half of the distribution of leverage across firms in 2010.

Immigrant Hiring and Capital Intensity. Having shown that German firms depend on debt to finance investment, and that initially higher-leverage ones face steeper financing-cost curves, I finally provide descriptive evidence that suggests that higher initial leverage makes it harder for firms to adjust their capital stocks when hiring immigrants. This analysis exploits the custom link between enterprise-level financial statements and establishment-level social security records, aggregating up all establishment-level measures to the enterprise level in the case of multi-establishment enterprises.

Using the custom link, I consider the following regression specification:

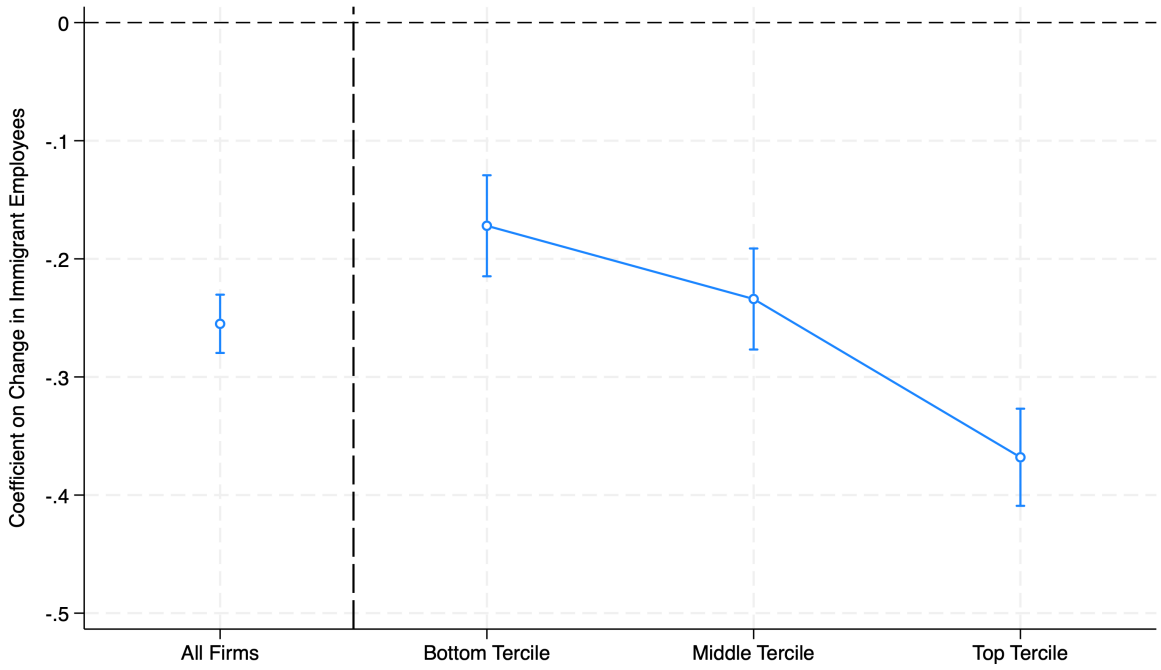
$$d \ln \left(\frac{K_j}{L_j} \right) = \sum_{k=1}^{3} \left(\alpha_k \mathbf{1}(T_{j0} = k) + \beta_k \mathbf{1}(T_{j0} = k) \frac{dL_j^{imm}}{L_{j0}} \right) + u_j \tag{7}$$

where $d \ln(K_j / L_j)$ is the change in firm j's log net tangible fixed assets per employee from 2010 to 2019; dL_j^{imm} / L_{j0} is the change in j's number of immigrant employees from 2010 to 2019 relative to its total number of employees in 2010; and $T_{j0} \in \{1, 2, 3\}$ is the tercile of the 2010 leverage distribution that j belongs to. The parameters of interest β_1, β_2, and β_3 describe a gradient of capital intensity responses to immigrant hiring.

$\beta_3 < \beta_2 < \beta_1 < 0$ would suggest that initially higher-leverage firms reduce their capital intensity by more when hiring immigrants. This pattern would be closely related to the first claim from part (d) of Proposition 2 from Section 2.2 that initially higher-leverage firms experience sharper declines in their capital intensity in response to immigration.

Figure 5 plots exactly this pattern, with $\beta_1 = -0.17$, $\beta_2 = -0.23$, and $\beta_3 = -0.37$. Thus, when hiring immigrants, the initially highest-leverage firms saw their capital intensity fall by about twice as much as the lowest-leverage ones, a difference that is statistically significant (Appendix Figure C11). This gradient in initial leverage also holds within other dimensions of firm heterogeneity, including sector (Appendix Figure C12), age (Appendix Figure C13), size (Appendix Figure C14), and skill intensity (Appendix Figure C15).[21] Firm leverage therefore seems to have a distinctively important role in shaping firms' capital intensity responses to hiring immigrants.

Figure 5: Sensitivity of Capital Intensity to Immigrant Hiring by Initial Leverage



Sources: Custom link between Moody's DataHub and Establishment History Panel.
Notes: This figure plots estimates of Equation (7), regressing a firm's change in log net tangible fixed assets per employee from 2010 to 2019 on the change in its number of immigrant employees relative to its total number of employees in 2010, interacted with the tercile of the 2010 leverage distribution that the firm belongs to. The first estimate for all firms is from a version of Equation (7) without the interactions. The figure plots 90% confidence intervals robust to heteroskedasticity.

[21] Firm sector and age are both based on the enterprise-level characteristics according to the data from Moody's DataHub. In contrast, firm size, referring to the number of employees, and skill intensity, referring to the university-educated share of employees, are both based on the aggregated establishment-level social security records from the Establishment History Panel.

4 Econometric Approach

This section introduces and validates the econometric approach that I take to identify the effects of local immigration shocks, based on which I formally test the predictions of the model developed in Section 2 and supplement the descriptive evidence presented in Section 3. Section 4.1 describes the regression specification that I use to first estimate the commuting zone-level effects of immigration. Section 4.2 develops the conditional shift-share identification strategy with which I address potential bias from immigrant selection into commuting zones. Section 4.3 states the regression specification with which I estimate the firm-level effects of market-level immigration shocks in Section 5.

4.1 Commuting Zone-Level Specification

I begin by characterizing the effect of an immigration-induced increase in labor supply on total employment at the commuting zone level, using only the data on workers' social security records from the IAB.[22] This effect relates to how immigration to Germany during the 2010s raised the denominator of the aggregate capital-labor ratio, whose concurrent decline I document in Section 3.3.

Consider the change in immigrant employment in commuting zone r from 2010 to 2019 relative to local total employment in 2010:

$$dX_r = \frac{L^{imm}_{r,2019} - L^{imm}_{r,2010}}{L_{r,2010}} = \frac{L^{imm}_{r,2019} - L^{imm}_{r,2010}}{L^{nat}_{r,2010} + L^{imm}_{r,2010}}$$

where $L^{imm}_{r,2010}$ and $L^{imm}_{r,2019}$ denote immigrant employment in r in 2010 and 2019, $L_{r,2010}$ and $L^{nat}_{r,2010}$ denote total and native employment in r in 2010, and employment is measured in full-time equivalent units as in Figure 1 from Section 3.2. I use the following regression to estimate the effect of this decadal inflow of immigrants on total employment:

$$\frac{L_{r,2019} - L_{r,2010}}{L_{r,2010}} = \alpha + \beta\, dX_r + \gamma' W_r + u_r \tag{8}$$

[22] I validate my approach to identifying the effects of local immigration shocks at the commuting zone level, rather than at the firm level, for two reasons. First, it is conceptually most natural to evaluate the market-level effects of a market-level shock, using only the local variation that identifies it. Second, and as a more practical matter, the IAB provides the two datasets that I use—the Sample of Integrated Labour Market Biographies, and the custom link between enterprise-level financial statements and establishment-level social security records—in two separate project folders on its data servers. While I can construct local immigration shocks using the worker-level data in the first folder and export them to the second folder containing the firm-level data, the IAB's statistical disclosure control requirements regarding the minimum number of worker-level observations necessary to export commuting zone-level aggregates prevent me from exporting each origin country's shares of local employment. I can therefore implement the overidentification tests necessary to validate my ethnic-enclave shift-share instrument (see Section 4.2) only at the commuting zone level.

where $(L_{r,2019} - L_{r,2010})/L_{r,2010}$ is the change in total employment in commuting zone r from 2010 to 2019 relative to local total employment in 2010, and W_r is a vector of potential control variables reflecting the pre-determined characteristics (i.e., in or before 2010) of employed natives along dimensions like age, education, gender, and sector. The parameter of interest is β, capturing the effect of a 1-percentage-point increase in local employment due to immigration on total employment growth, measured relative to initial total employment. Likewise, $\beta - 1$ reflects the effect of this increase in immigrant employment on native employment, also measured relative to initial total employment. To focus on the effect on the average worker, I weight each commuting zone r by its share of total nationwide employment in 2010 (i.e., $L_{r,2010}/\sum_{r'} L_{r',2010}$).

I define commuting zones starting from the 141 local labor markets identified by Kosfeld and Werner (2012) using data on how workers commute from their homes to their workplaces across German counties. To satisfy the IAB's statistical disclosure control requirements that each commuting zone-level immigration shock reflect the individual-level observations of at least 20 immigrant workers, I further aggregate adjacent local labor markets into 117 final commuting zones (see Appendix Section B.1).

The residual term u_r in Equation (8) captures other shocks to local total employment that may also be correlated with the local inflows of immigrants dX_r. In particular, if positive local demand shocks increase native employment in certain commuting zones while also attracting immigrants newly arriving in Germany, then $Cov[u_r, dX_r|W_r] > 0$. The ordinary least squares estimator (OLS) of β is therefore likely to be biased upward.

4.2 Conditional Shift-Share Identification

To address the OLS estimator's bias from immigrants selecting into local labor markets, I exploit variation in the settlement patterns of earlier immigrants as far back as 1993, the earliest year for which the data on workers' social security records is complete for reunified Germany (Schmucker and Berge, 2025). In particular, I consider a shift-share instrumental variable estimator (SSIV) that instruments the local inflows of immigrants dX_r with the following ethnic-enclave shift-share instrument in the style of Card (2009):

$$Z_r^{SSIV} = \sum_o \left(\overbrace{\frac{\tilde{L}_{r,o,1993}}{\tilde{L}_{r,1993}}}^{o\text{'s local share: } s_{r,o}} \times \underbrace{\frac{L_{o,2019} - L_{o,2010}}{L_{o,2010}}}_{o\text{'s nationwide shift: } g_o} \right) \tag{9}$$

where o indexes origin countries, $\tilde{L}_{r,o,1993}$ is the number of immigrants from o employed in commuting zone r in 1993, $\tilde{L}_{r,1993}$ is the total number of employees in r in 1993, $s_{r,o}$ is o's share of the total number of employees in r in 1993, $L_{o,2010}$ and $L_{o,2019}$ denote

the full-time equivalent employment nationwide of immigrants from o, and g_o is the nationwide shift in employment from o from 2010 to 2019.[23] Thus, the ethnic-enclave shift-share instrument Z_r^{SSIV} is a particular weighted sum across origin countries of their shares $s_{r,o}$ of local employment in 1993, with the shifts g_o reflecting the scale of their immigrants' nationwide inflows into the German labor market from 2010 to 2019.

Assuming a strong first stage, I argue for the validity of the instrument Z_r^{SSIV} in terms of the conditional exogeneity of the origin country-specific shares $s_{r,o}$; this is in contrast to an alternative approach that assumes the exogeneity of the origin country-specific shifts g_o but that also requires controlling for the overall immigrant share of local employment (Borusyak et al., 2022).[24] Based on the exogenous-shares approach recently formalized by Goldsmith-Pinkham et al. (2020), my identifying assumption is as follows:

$$\forall o \text{ such that } g_o \neq 0: \quad E[u_r s_{r,o} | W_r] = 0 \tag{10}$$

The assumption in Equation (10) states that the local labor demand shocks that attracted the immigrants newly arriving in Germany during the 2010s to certain commuting zones were uncorrelated with the settlement patterns of earlier immigrants in 1993, conditional on the vector of control variables W_r. To make this assumption more plausible, my baseline specification includes in W_r a rich set of historical native characteristics, namely, the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993.

A common argument for why Equation (10) might be satisfied is that more recent shocks were uncorrelated with the past shocks that had attracted the earlier immigrants (Card, 2009; Dustmann et al., 2013). In my setting, this argument is aided by the fact that the shares are defined eighteen years prior to the 2011 onset of the immigration shock, and by the sector composition of earlier immigrants back then differing considerably from that of recent immigrants during the 2010s (see Appendix Table C2).

I next implement the validity tests recommended by Goldsmith-Pinkham et al. (2020) relating to overidentification, the sensitivity of estimates to the inclusion of alternative controls, and pretrends. In particular, I document and suggest a solution to challenges in my setting related to their overidentified interpretation of the shift-share instrument.

[23] The shares $s_{r,o}$ are based on the number of employees rather than full-time equivalent employment to focus more naturally on immigrants' geographic preference for where there are more of their compatriots, rather than where more of their compatriots work more hours.

[24] The shift-based interpretation of the validity of the ethnic-enclave shift-share instrument is challenged in the setting of Germany by the fact that earlier immigrants from different origin countries tend to be settled in similar places. As a result, controlling for the overall immigrant share of local employment leaves little identifying variation in the instrument's first stage.

Overidentification Tests. Under the exogenous-shares interpretation of the shift-share instrument, the SSIV estimator is overidentified (Goldsmith-Pinkham et al., 2020): there are more instruments $s_{r,o}$, one for each origin country o included in the construction of the instrument Z_r^{SSIV} according to Equation (9), than there are endogenous regressors, of which there is only one, dX_r, in Equation (8). In my setting, I construct Z_r^{SSIV} from all 74 of the origin countries that satisfy the IAB's statistical disclosure requirements that there be at least 20 worker-level observations in every year.

This setting makes it possible to test for the violation of the overidentifying restrictions in Equation (10) by implementing appropriate J-tests, which evaluate whether the residuals u_r from Equation (8) are correlated with the origin country-specific shares $s_{r,o}$. With no ex-ante reason to make the restrictive assumption that these residuals are homoskedastic, I allow for heteroskedasticity and therefore focus on the heteroskedasticity-robust J-tests recommended by the literature (Hansen, 1982; Hansen et al., 1996; Chao et al., 2014; Goldsmith-Pinkham et al., 2020). In particular, I implement the J-tests associated with the heteroskedasticity-robust limited information maximum likelihood estimator (HLIM), the heteroskedasticity-robust Fuller estimator (HFUL), the two-step efficient generalized method of moments estimator (EGMM), and the continuously updating generalized method of moments estimator (CUE). Table 1 reports the results of these J-tests. All of their p-values exceed 0.3, so they fail to reject the null hypothesis that the overidentifying restrictions are valid.[25] These results are consistent with the validity of my conditional shift-share identification strategy.

Table 1: Robust J-Tests for the Effect of Immigration on Total Employment

	HLIM (1)	HFUL (2)	EGMM (3)	CUE (4)
J-test p-value	0.321	0.318	0.571	0.650
No. commuting zones	117	117	117	117

Sources: Sample of Integrated Labour Market Biographies.
Notes: This table reports the p-values from heteroskedasticity-robust J-tests for the commuting zone-level effect of immigration on total employment, based on different overidentified estimators of Equation (8) that use as instruments the 74 origin country-specific shares of local employment included in the construction of the ethnic-enclave shift-share instrument defined by Equation (9). Column (1) considers the heteroskedasticity-robust limited information maximum likelihood estimator (HLIM). Column (2) considers the heteroskedasticity-robust Fuller estimator (HFUL). Column (3) considers the two-step efficient generalized method of moments estimator (EGMM). Column (4) considers the continuously updating generalized method of moments estimator (CUE).

[25] In contrast, the J-tests based on the two-stage least squares estimator (TSLS) and limited information maximum likelihood estimator (LIML) do reject this null hypothesis (Appendix Table D1). However, these tests are known to over-reject under heteroskedasticity.

In addition to the formal overidentification tests in Table 1, Goldsmith-Pinkham et al. (2020) recommend the following visual test. On the vertical axis, plot the second-stage estimate based on the just-identified estimator for each origin country-specific share $s_{r,o}$. On the horizontal axis, plot the corresponding first-stage F-statistic for that estimator. Finally, size each point by the weight assigned to it by the SSIV estimator, which the authors show can be written as a weighted average of different just-identified estimators across origin countries. The plot therefore visualizes the contributions of the different estimators to the weighted-average estimate yielded by the SSIV estimator, as well as whether those contributions come from shares with weak first stages.

Figure 6a illustrates this plot for the effect of immigration on total employment based on Equation (8), visualizing the second-stage estimate yielded by the just-identified estimator for each origin country-specific share, its corresponding first-stage F-statistic, and the weight assigned to it by the SSIV estimator. The plot highlights a potential issue with the SSIV estimator in my setting: its weighted-average estimate lies below almost all the second-stage estimates with first-stage F-statistics exceeding the usual threshold of 10, dragged down by a negative estimate from aggregating across shares with first-stage F-statistics below this threshold. The weak instruments, whose second-stage estimates have been shown to be unreliable (Bound et al., 1995; Shea, 1997; Staiger and Stock, 1997; Stock and Yogo, 2005), thus appear to bias the entire SSIV estimate downward relative to the strong instruments' more reliable second-stage estimates.

To make sense of the issue in Figure 6a, in Appendix Section D.1, I derive the following representation of the Rotemberg weight (Goldsmith-Pinkham et al., 2020) assigned by the SSIV estimator to the just-identified estimator for each origin country-specific share:

$$\alpha_o^{SSIV} = \frac{\frac{g_o \hat{R}_o^2}{\hat{\pi}_o}}{\sum_{o'} \frac{g_{o'} \hat{R}_{o'}^2}{\hat{\pi}_{o'}}} \tag{11}$$

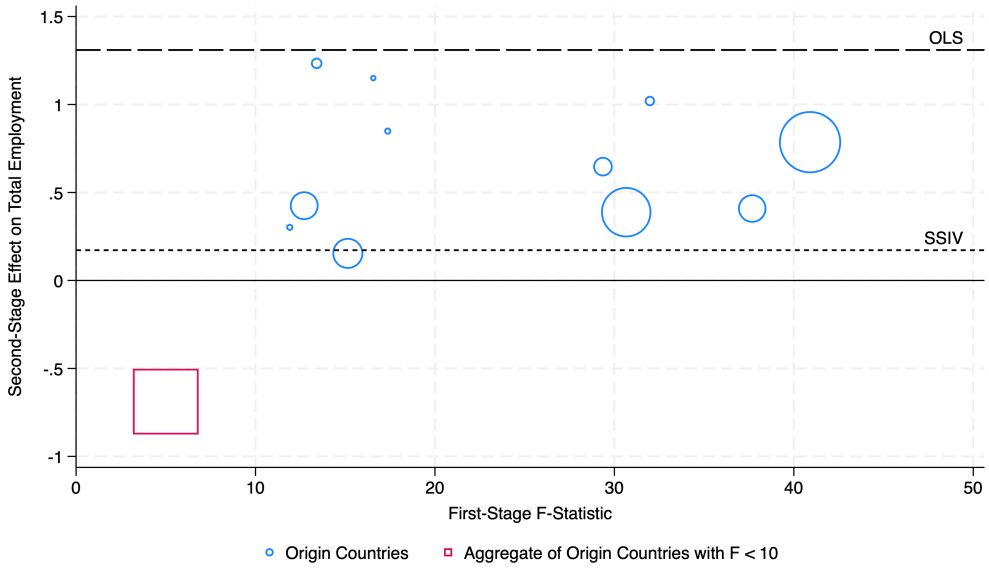
where g_o is the nationwide shift for origin country o, $\hat{R}_o^2$ is the estimated R^2 from the regression of the endogenous regressor dX_r on o's local share $s_{r,o}$ after partialing out the effects of the controls W_r, and $\hat{\pi}_o$ is the estimated first-stage coefficient from this regression. In Appendix Section D.1, I also derive the weight assigned by the two-stage least squares estimator (TSLS) if the covariance structure of the shares is ignored:[26]

$$\alpha_o^{TSLS} = \frac{\hat{R}_o^2}{\sum_{o'} \hat{R}_{o'}^2} \tag{12}$$

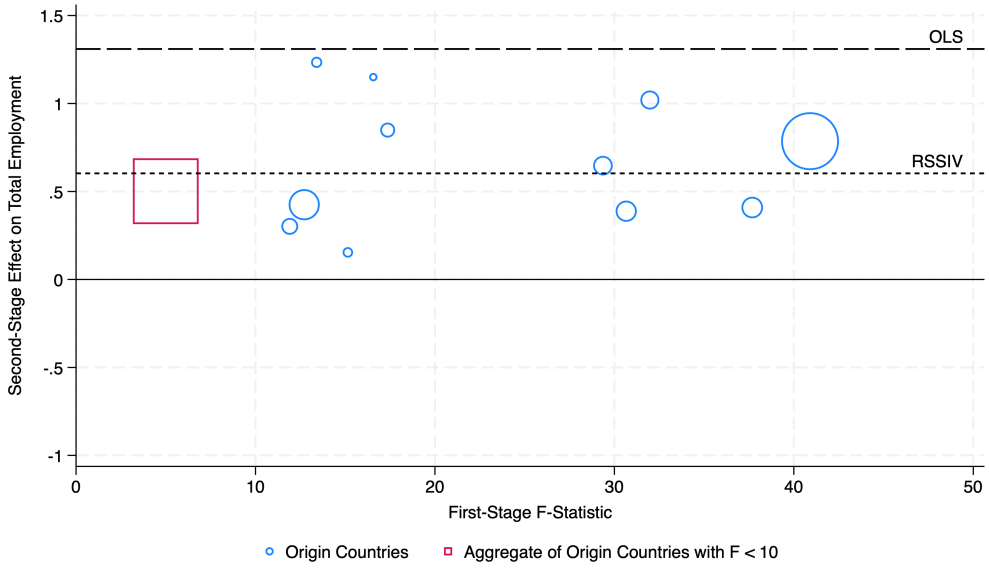
[26] The TSLS weight in the case of orthogonal instruments is the relevant benchmark for the SSIV weight, as the SSIV estimator ignores the covariance structure of the shares.

Figure 6: Visual Tests for the Effect of Immigration on Total Employment

(a) Shift-Share Instrumental Variable Estimator



(b) Reweighted Shift-Share Instrumental Variable Estimator



Sources: Sample of Integrated Labour Market Biographies.
Notes: This figure plots the visual overidentification test recommended by Goldsmith-Pinkham et al. (2020). Panel (a) illustrates the plot for the shift-share instrumental variable estimator (SSIV) based on the instrument defined in Equation (9). Panel (b) illustrates the plot for the reweighted shift-share instrumental variable estimator (RSSIV) based on the instrument defined in Equation (13). The vertical axis plots the second-stage estimate based on the just-identified estimator for each origin country-specific share $s_{r,o}$. The horizontal axis plots the corresponding first-stage F-statistic for that estimator. Each point is sized by the weight assigned to it by the corresponding estimator. Circles indicate individual origin countries, none of which is assigned a negative weight. The square indicates the estimate from aggregating across shares with first-stage F-statistics below 10. Each panel plots the resulting weighted average across just-identified estimates as well as the ordinary least squares estimate (OLS).

A comparison of Equations (11) and (12) yields a key insight: the SSIV estimator under-penalizes weak instruments by a factor of $\hat{\pi}_o$ relative to the TSLS estimator (in the case of orthogonal instruments). This suggests a potential solution to the issue in Figure 6a of weak instruments biasing the SSIV estimate away from the strong instruments' more reliable second-stage estimates: reweight each origin country-specific share by a factor of $\hat{\pi}_o$. I therefore consider a reweighted shift-share instrumental variable estimator (RSSIV) based on an ethnic-enclave shift-share instrument modified as follows:

$$Z_r^{RSSIV} = \sum_o s_{r,o} g_o \hat{\pi}_o \tag{13}$$

The Rotemberg weights assigned by the RSSIV estimator are then:

$$\alpha_o^{RSSIV} = \frac{g_o \hat{R}_o^2}{\sum_{o'} g_{o'} \hat{R}_{o'}^2} \tag{14}$$

where $\hat{R}_o^2$ in Equation (14) has simply replaced $\hat{R}_o^2 / \hat{\pi}_o$ in Equation (11) in determining how the estimator accounts for each origin country-specific share's first stage.

Figure 6b recreates the plot illustrated in Figure 6a but now with each point sized, and the weighted average calculated, based on the weights assigned to it by the RSSIV estimator rather than the SSIV estimator. The weighted average now falls in the middle of the second-stage estimates with first-stage F-statistics exceeding the usual threshold of 10. Moreover, the estimate from aggregating across shares with first-stage F-statistics below this threshold now aligns with the strong instruments' more reliable second-stage estimates, unlike in Figure 6a. Thus, as expected, the weighted average underlying the RSSIV estimate appears to be based on more reasonable weights.

In the rest of this paper, I focus on RSSIV estimates yielded by instrumenting the local inflows of immigrants dX_r with the reweighted ethnic-enclave shift-share instrument defined in Equation (13). This choice is justifiable for three reasons. The first is based on the above discussion of the differences between Figures 6a and 6b: weak instruments pull the SSIV estimate away from the central tendency of the estimates yielded by strong instruments. Second, Appendix Table D2 shows that, relative to the SSIV estimate of the effect of immigration on total employment, the RSSIV estimate is much closer to estimates based on overidentified estimators that have been shown to be robust to many weak instruments (Chao et al., 2014; Goldsmith-Pinkham et al., 2020). Finally, choosing the reweighted estimator is compatible with the results of the J-tests reported in Table 1: given their failure to reject the null hypothesis that the overidentifying restrictions in Equation (10) are valid, my reweighting yields an equally valid weighted-average estimate as the conventional weighting.

This last point raises the question of whether the particular reweighting in Equation (13) is preferable. A comparison of Equations (11) and (12) suggests that the Rotemberg weight assigned to each origin country-specific share $s_{r,o}$ by the SSIV estimator matches that assigned by the TSLS estimator if the origin country-specific shift g_o is proportional to the just-identified first-stage coefficient $\hat{\pi}_o$. The rationale for a particular choice of shifts in the exogenous-shares setting may therefore be that a larger shift should capture its corresponding share's better ability to predict inflows of observed immigrants.

However, where standard shifts do not reflect just-identified first-stage power in this exact way, one could also consider doing away with these shifts entirely. Instead, define a reweighted share instrumental variable (RSIV) to ensure its Rotemberg weights are given by Equation (12), based only on the just-identified first-stage partial R^2, $\hat{R}^2_o$:

$$Z_r^{RSIV} = \sum_o s_{r,o}\hat{\pi}_o \tag{15}$$

Appendix Table D3 shows that the RSSIV and RSIV estimates of the effect of immigration on total employment closely resemble each other.[27] I conclude my discussion of instrument choice here and move on to the remaining validity tests.

Sensitivity to the Inclusion of Alternative Controls. Table 2 reports both OLS and instrumental variable (IV) estimates, the latter based on the RSSIV estimator, of the effect of immigration from 2010 to 2019 on total employment based on Equation (8). Column (1) includes no control variables in the vector W_r, resulting in OLS and IV estimates that both exceed 1, which would imply that immigration actually increased native employment. Although the IV estimate is statistically significantly smaller than the OLS estimate, suggesting that it addresses some of the latter's positive bias, both of these estimates likely remain biased upward due to omitted variables.

After column (2) controls for the ages 50–64 share of employed natives in 2010, the IV estimate falls to a still statistically significant 0.6, which suggests that native demographic decline is a key omitted variable. The difference between columns (1) and (2) implies that both total employment growth and immigration were correlated with the initial share of natives near retirement, leading to the upward-biased estimates in column (1).

[27] In contrast to the similar RSSIV and RSIV estimates of the total employment effect of immigration at the commuting zone level, Appendix Table D3 shows that the RSSIV estimate of the effect of immigration on mean wages is less negative than the RSIV estimate. Unlike in Figure 6b, where the estimates of the total employment effect based on the strongest instruments are dispersed around their central tendency, Figure D1b shows that the estimate of the mean wage effect based on the strongest instrument lies above the estimates based on the other strong instruments. Since the RSSIV estimator happens to assign this strongest instrument a larger weight than the RSIV estimator, the RSSIV estimate is pulled upward relative to the RSIV estimate. Given this difference, my discussion in Section 5 of the firm-level wage effects of immigration focuses on the RSSIV estimates but also refers to the RSIV estimates.

The origin country-specific shares of local employment used to construct the ethnic-enclave shift-share instrument are defined in 1993, so it would be preferable to identify native characteristics in 1993 that predict the same native demographic decline as the ages 50–64 share in 2010. Column (3), which instead controls for the ages 15–29, ages 30–49, and university-educated shares of employed natives in 1993, suggests that these historical shares are appropriate replacements: the IV estimate remains almost unchanged. To test for any remaining omitted variable bias, column (4) additionally controls for the apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. The IV estimate again remains essentially unchanged. The remainder of this paper includes all six of the control variables in column (4) in the vector W_r, accounting for a sparse but key set of potential confounders related to the age, education, gender, and sector characteristics of local labor forces.

Comparing Panels (a) and (b) across columns also clarifies what these control variables address. While the OLS estimates remain between 1.2 and 1.6 regardless of the controls, the IV estimates fall by more than half once the native age structure is accounted for. The controls therefore matter primarily for the validity of the instrument: commuting zones with larger historical immigrant enclaves differed in their native age structure in ways that independently affected their employment growth. Once these differences are accounted for, Panel (c) shows that the OLS estimate consistently exceeds the IV estimate by about 0.7, consistent with immigrants selecting into commuting zones with stronger contemporaneous labor demand.

Controlling for historical rather than initial native characteristics weakens the first stage, with the first-stage F-statistic falling from 224 in column (2) to 55 in column (3) and 51 in column (4). Nevertheless, since my specification includes a single instrument (albeit a shift-share one that represents a weighted sum of many origin country-specific instruments), this heteroskedasticity-robust F-statistic coincides with the effective F-statistic of Montiel Olea and Pflueger (2013), and it remains well above their critical value of 23.1 for a worst-case bias of 10% of the OLS bias.

My analysis of Table 2 concludes by interpreting the magnitude of the IV estimate of 0.6 that is robust across columns (2)–(4). This point estimate implies that a commuting zone experiencing a 10-percentage-point increase in immigrant employment relative to initial total employment, about the scale of the nationwide shock during the 2010s, saw only a 6-percentage-point increase in total employment relative to a commuting zone with no such increase. It thus also implies a 4-percentage-point decline in native employment relative to the same denominator, a negative effect on native employment that would be consistent with firms' capital stocks failing to keep up with the immigration-induced increase in labor supply (see Section 3.3).

Table 2: Effect of Immigration from 2010 to 2019 on Total Employment

	Change in Total Employment Relative to Initial Total Employment			
Change in immigrant employment relative to initial total employment	(1)	(2)	(3)	(4)
Panel (a): OLS	1.559*** (0.147)	1.245*** (0.278)	1.296*** (0.255)	1.310*** (0.107)
Panel (b): IV	1.313*** (0.142)	0.594*** (0.176)	0.567** (0.267)	0.603** (0.280)
First-stage F-statistic	298.32	224.32	54.96	50.89
First-stage partial R^2	0.648	0.457	0.431	0.408
Panel (c): OLS − IV	0.246** [0.039]	0.651** [0.015]	0.729** [0.034]	0.707** [0.014]
Controls:				
Ages 50–64 share in 2010	No	Yes	No	No
Ages 15–29 share in 1993	No	No	Yes	Yes
Ages 30–49 share in 1993	No	No	Yes	Yes
University-educated share in 1993	No	No	Yes	Yes
Apprenticeship-trained share in 1993	No	No	No	Yes
Female share in 1993	No	No	No	Yes
Manufacturing share in 1993	No	No	No	Yes
No. commuting zones	117	117	117	117

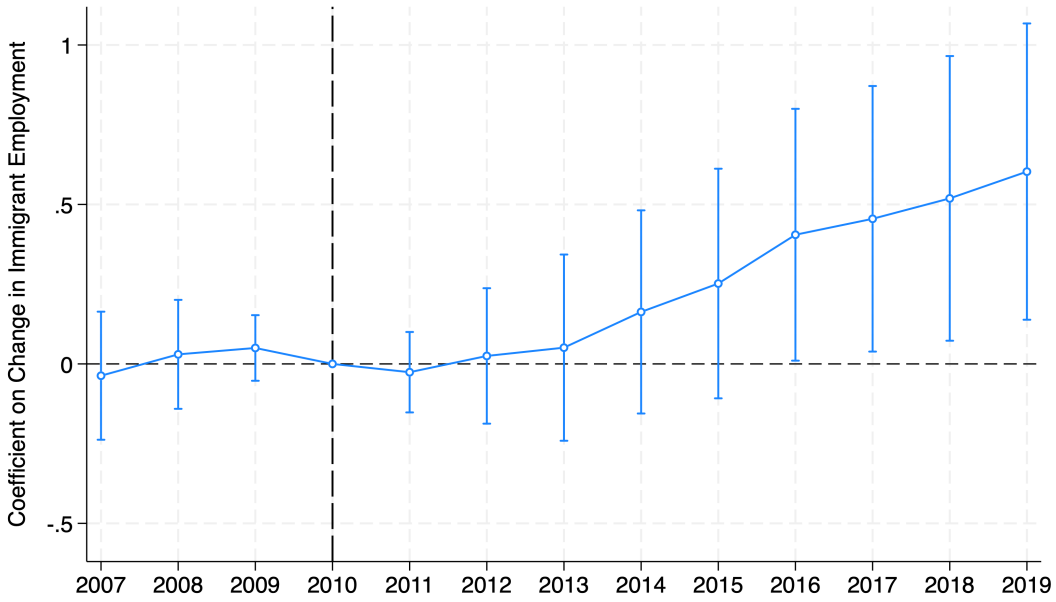
Sources: Sample of Integrated Labour Market Biographies.
Notes: This table reports estimates of the commuting zone-level effect of immigration from 2010 to 2019 on total employment, based on different specifications of Equation (8) that use different vectors of control variables. Panel (a) reports ordinary least squares estimates (OLS). Panel (b)'s instrumental variable (IV) estimates are based on the reweighted ethnic-enclave shift-share instrument defined in Equation (13). Panel (c) reports the differences between the OLS and IV estimates. Column (1) considers no controls. Column (2) controls for the ages 50–64 share of employed natives in 2010. Column (3) instead controls for the ages 15–29, ages 30–49, and university-educated shares of employed natives in 1993. Column (4) additionally controls for the apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. Commuting zones are weighted by their 2010 shares of nationwide employment. Standard errors are robust to heteroskedasticity and reported in parentheses, while p-values are reported in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Pretrends and Other Commuting Zone-Level Outcomes. The last validity test recommended by Goldsmith-Pinkham et al. (2020) evaluates pretrends. Keeping the immigration shock at the decadal horizon from 2010 to 2019 while allowing the coefficients on it and the control variables to vary with the horizon of the outcome variable, I now consider as the outcome the change in total employment from 2010 to year t relative to total employment in 2010 for every $t \in \{2007, \ldots, 2019\}$.

Figure 7 plots the resulting estimates. Commuting zones that faced local immigration shocks of different scales after 2010 did not seem to be on different pretrends, which is reassuring for my conditional shift-share identification strategy. Interestingly, total employment did not appear to grow in response to immigration during the first three years of the 2010s. Nevertheless, total employment gradually expanded starting in 2014, reaching the IV estimate of 0.6 from column (4) of Table 2 by 2019.

Appendix Figure D2 plots the same dynamic effects but now on the change in the mean log wage relative to 2010. Pretrends were again limited, and immigration's wage effect was negative at the commuting zone level by 2019.

Figure 7: Dynamic Effects of Immigration from 2010 to 2019 on Total Employment



Sources: Sample of Integrated Labour Market Biographies.
Notes: This figure plots instrumental variable estimates of the commuting zone-level effects of immigration from 2010 to 2019 on the relative change in total employment from 2010 to each year, based on Equation (8) and the reweighted ethnic-enclave shift-share instrument defined in Equation (13). The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. Commuting zones are weighted by their 2010 shares of nationwide employment. The figure plots 90% confidence intervals robust to heteroskedasticity.

4.3 Firm-Level Specification

Having characterized the commuting zone-level effects of immigration, I now turn to evaluating the effects of market-level shocks at the firm level using the custom link between enterprise-level financial statements and establishment-level social security records. Adapting Equation (8), I regress the change dY_j in an outcome for firm j on the local inflows of immigrants into the commuting zone $r(j)$ in which it operates:

$$dY_j = \alpha + \beta \overbrace{\frac{L^{imm}_{r(j),2019} - L^{imm}_{r(j),2010}}{L_{r(j),2010}}}^{dX_{r(j)}} + \gamma' W_j + u_j \tag{16}$$

where $dX_{r(j)}$ is the change in immigrant employment in firm j's commuting zone $r(j)$ from 2010 to 2019 relative to local total employment in 2010, and W_j is a vector of predetermined control variables. In W_j, I include all the historical characteristics of natives in commuting zone $r(j)$ included in my baseline specification in Section 4.2, namely, the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. I also include fixed effects for cells of firms defined by their initial characteristics, which accounts for any nationwide shocks or trends common to particular types of firms in different commuting zones.[28]

Since $dX_{r(j)}$ is a market-level inflow, I cluster standard errors at the commuting zone level. Furthermore, I weight each firm j by its share of the total number of employees in its commuting zone $r(j)$ in 2010, while still weighting each commuting zone by its same share of total nationwide employment in 2010 that I use as its weight in Section 4.1. Having already shown in Table 2 that the OLS estimates of the commuting zone-level effects are biased upward, I focus on the IV estimates of the parameter of interest β in Equation (16), instrumenting $dX_{r(j)}$ with the corresponding reweighted ethnic-enclave shift-share instrument $Z^{RSSIV}_{r(j)}$ for commuting zone $r(j)$ defined in Equation (13). To analyze the heterogeneous effects of immigration by firm leverage, I also estimate a version of Equation (16) where β is allowed to vary by the tercile of the 2010 leverage distribution in which each firm ranks, interacting both the endogenous regressor $dX_{r(j)}$ and the instrument $Z^{RSSIV}_{r(j)}$ with a dummy variable for each tercile.

Based on the model developed in Section 2, the outcome variables that I consider when estimating Equation (16) are the change in firm j's number of immigrant employees from 2010 to 2019 relative to its total number of employees in 2010; the change in its log

[28] The characteristics include a firm's sector (see the sectors listed in Appendix Table C2), cohort (whether it first appears after 2000, from 1996 to 2000, or in or before 1995), and terciles in the distributions across firms of size (number of employees), skill intensity (university-educated share), and leverage (ratio of long-term debt to total assets) in 2010. The fixed effects are for the interactions of these characteristics.

net tangible fixed assets per employee from 2010 to 2019; the symmetric growth rate of its long-term debt from 2010 to 2019; the change in the log mean wage of its full-time employees from 2010 to 2019; the change in its number of native employees from 2010 to 2019 relative to its total number of employees in 2010; and the change in the log mean wage of its native full-time employees from 2010 to 2019.[29] I consider firms for which I can calculate all of these changes, so that the composition of firms is fixed. To ensure that outliers do not drive my estimates, I apply a standard 1% winsorization (Imbert et al., 2022; Brinkmann and Wolter, 2026; Liang, 2026).

The unit of firms that I consider when estimating Equation (16) is the establishment, as that is the level at which inflows of immigrants into local labor markets shape firms' production choices. If an enterprise is mapped to multiple establishments, I distribute each item on its balance sheet in proportion to the number of employees at each of its establishments. My final sample includes 140,973 establishments.

5 Firm-Level Effects of Immigration

This section estimates the effects of market-level immigration shocks on firms, formally testing the predictions of the model developed in Section 2. Section 5.1 summarizes the outcome variables that I consider and describes the relationship of firm leverage to other firm characteristics. Section 5.2 reports estimates of the average firm-level effects of immigration based on the regression specified in Equation (16). Section 5.3 characterizes how these effects vary with firm leverage.

5.1 Summary Statistics

Table 3 summarizes the mean and standard deviation of the changes in firms' outcomes from 2010 to 2019 and of their leverage in 2010. At the average firm, the number of immigrant employees increased by 9 percentage points relative to the total number of employees in 2010, similar to the 10-percentage-point increase in economy-wide immigrant employment relative to total employment in 2010 (see Section 3.2). The average firm also saw its capital intensity and debt decline, while the wages and employment of its workers grew.[30] Finally, 32% of the average firm's total assets in 2010 were funded by long-term debt, with a standard deviation of similar magnitude, suggesting considerable variation across firms in their initial leverage.

[29] Mean wages are available only for full-time employees. Considering the symmetric growth rate of debt $(D_{j,2019} - D_{j,2010})/(0.5D_{j,2010} + 0.5D_{j,2019})$ ensures that firms with no debt in 2010 are not dropped.

[30] That wages and native employment grew at the same time as firms' capital intensity and debt fell can be explained by the tight labor market in Germany during the 2010s, driven by both native demographic decline and a strong macroeconomic environment (Dustmann et al., 2026).

Table 3: Summary Statistics of Key Firm-Level Variables

	Mean (1)	Standard Deviation (2)
Changes from 2010 to 2019:		
Immigrant employees relative to initial employees	0.092	0.218
Log net tangible fixed assets per employee	−0.083	1.038
Symmetric growth rate of long-term debt	−0.203	1.453
Log mean wage of full-time employees	0.133	0.192
Native employees relative to initial employees	0.332	0.891
Log mean wage of native full-time employees	0.142	0.199
Level in 2010:		
Leverage (long-term debt to total assets)	0.320	0.323
No. firms	140,973	

Sources: Custom link between Moody's DataHub and Establishment History Panel.
Notes: This table summarizes the mean and standard deviation of key firm-level variables considered in the estimation of Equation (16). The variables are the change in firm j's number of immigrant employees from 2010 to 2019 relative to its total number of employees in 2010; the change in its log net tangible fixed assets per employee from 2010 to 2019; the symmetric growth rate of its long-term debt from 2010 to 2019; the change in the log mean wage of its full-time employees from 2010 to 2019; the change in its number of native employees from 2010 to 2019 relative to its total number of employees in 2010; the change in the log mean wage of its native full-time employees from 2010 to 2019; and the ratio of its long-term debt to total assets in 2010. All variables have been winsorized at the 1st and 99th percentiles.

To describe how leverage is related to other firm characteristics, Table 4 reports estimates from regressions of each firm's leverage in 2010 on separate sets of dummies (without a constant) for sector categories, cohorts, and terciles of initial size and skill intensity. Panel (a) shows that, on average, firms in the low-skill sectors into which immigrants sorted (see Appendix Table C2) had higher leverage in 2010 than firms in manufacturing or high-skill sectors. Similarly, panels (b) and (c) show that leverage was higher at younger and smaller firms, respectively. The former result is consistent with studies showing that firms switch from external to internal financing as they age (Dinlersoz et al., 2024; Kochen, 2025); the latter differs from evidence for a positive size-leverage relationship among private firms in the United States (Dinlersoz et al., 2024), although evidence from Europe is more mixed (Kochen, 2025). Panel (d) finally documents a negative relationship between a firm's skill intensity and its leverage, consistent with the result in panel (a) and with other studies (Liu et al., 2023; Sanati, 2025). Nevertheless, across all these other dimensions of firm heterogeneity, mean leverage ranges only from 0.30 to 0.35. This range is small relative to the standard deviation of 0.32 reported in Table 3, suggesting that leverage may be a distinct dimension of firm heterogeneity.

Table 4: Mean Leverage along Other Dimensions of Firm Heterogeneity

	Mean Leverage in 2010
Panel (a): By sector	
Manufacturing	0.313 (0.002)
Low-skill sectors	0.330 (0.001)
High-skill sectors	0.303 (0.002)
Panel (b): By cohort	
Founded after 2000	0.349 (0.002)
Founded from 1996 to 2000	0.315 (0.002)
Founded in or before 1995	0.305 (0.001)
Panel (c): By size in 2010	
Bottom tercile	0.330 (0.002)
Middle tercile	0.328 (0.002)
Top tercile	0.304 (0.001)
Panel (d): By skill intensity in 2010	
Bottom tercile	0.340 (0.002)
Middle tercile	0.324 (0.001)
Top tercile	0.297 (0.001)
No. firms	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel.
Notes: This table reports estimates from regressions of each firm's ratio of long-term debt to total assets in 2010 on separate sets of dummies (without a constant) for sector categories, cohorts, and terciles of initial size and skill intensity. Panel (a) considers dummies for the manufacturing sector, low-skill sectors (accommodation and food services, construction, transportation and storage, administrative and support services, wholesale and retail trade, and other services), and high-skill sectors (all others listed in Appendix Table C2). Panel (b) considers dummies for firms founded after 2000, from 1996 to 2000, and in or before 1995. Panel (c) considers dummies for terciles of the distribution of firms' number of employees in 2010. Panel (d) considers dummies for terciles of the distribution of firms' university-educated share of employees in 2010. Leverage has been winsorized at the 1st and 99th percentiles to address outliers. Standard errors are robust to heteroskedasticity and reported in parentheses.

5.2 Average Effects

Table 5 presents the IV estimates of the average effects of immigration based on Equation (16). Column (1) reports the effect of local inflows of immigrants $dX_{r(j)}$ from 2010 to 2019 on the change in firm j's immigrant employees over the same horizon relative to its total employees in 2010. The estimated coefficient is 1.1; that it is statistically indistinguishable from 1 implies that, on average, the firms in the sample hired immigrants at a rate close to that at which immigrants entered their local labor markets, a result that provides reassurance about the representativeness of the sample.

Column (2) shows that, in response to a 10-percentage-point increase in local immigrant employment relative to initial total employment, the average firm's log net tangible fixed assets per employee fell by 7.3%. This result suggests that immigration contributed to a decline in German firms' capital intensity during the 2010s. The model developed in Section 2 would then predict that, insofar as more capital increases the marginal

Table 5: Average Firm-Level Effects of Immigration from 2010 to 2019

	Immigrant Employees (1)	Log Capital per Employee (2)	Log Mean Wage (3)	Native Employees (4)
Local immigration $dX_{r(j)}$	1.124^{***}	-0.732^{**}	-0.238^{*}	-0.418^{**}
	(0.131)	(0.354)	(0.133)	(0.166)
No. commuting zones	117	117	117	117
No. firms	140,973	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the average firm-level effect of immigration from 2010 to 2019, based on the regression specified in Equation (16) and instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted ethnic-enclave shift-share instrument defined in Equation (13). Column (1) considers as the outcome variable the change in firm j's number of immigrant employees from 2010 to 2019 relative to its total number of employees in 2010. Column (2) considers the change in the firm's log net tangible fixed assets per employee from 2010 to 2019. Column (3) considers the change in the log mean wage of its full-time employees from 2010 to 2019. Column (4) considers the change in its number of native employees from 2010 to 2019 relative to its total number of employees in 2010. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

productivity of labor, this decline in firms' capital intensity would have also decreased the marginal productivity of labor. As a result, it would have negatively affected firms' workers. Columns (3) and (4) provide evidence consistent with this prediction, showing that the same increase in local immigrant employment decreased the mean wages of firms' workers by 2.4% and their number of native employees by 4.2 percentage points relative to their initial total number of employees.

The estimated coefficient for the average firm's symmetric growth rate of debt from 2010 to 2019, omitted in Table 5 for visual parsimony but reported in Table 8 below, is a statistically insignificant 0.3. Thus, the average firm did not appear to borrow in response to local immigration. This result is potentially related to the negative effect on capital intensity reported in column (2), insofar as German firms tend to finance capital investment by borrowing (see Section 3.4). I therefore next turn to exploring the heterogeneous effects of immigration by firms' initial leverage.

5.3 Heterogeneous Effects

Immigrant Hiring. I first test part (c) of Proposition 2 from Section 2.2, which predicts that differences between firms in their initial leverage should not lead to meaningful differences in their rates of hiring immigrants.[31] Column (1) of Table 6 repeats the estimated coefficient of 1.1, taken from column (1) of Table 5, for the average effect of immigration on firm-level immigrant hiring. Column (2) shows that this coefficient was 1.1–1.2 for all firms regardless of the tercile of the 2010 leverage distribution that they belonged to, and that there was no monotonic gradient in these estimates. Column (3) then shows that, although the estimate for the middle tercile differed from that of the bottom tercile at the 10% significance level, the estimates for the bottom and top terciles were statistically indistinguishable. Together, the results in Table 6 are consistent with my model's prediction that a firm's initial leverage does not impair its ability to respond to a market-level immigration shock by hiring the newly arriving immigrants.

Importantly, the results in Table 6 do not imply that all different types of firms hired immigrants at the same rate. Indeed, Appendix Tables E1–E4 show that firms in low-skill sectors, younger firms, smaller firms, and less skill-intensive firms responded to market-level immigration shocks by hiring newly arriving immigrants at higher rates than other firms. Since these same types of firms also tended to have higher initial leverage (see Table 4), the absence of a leverage gradient in Table 6 is not an artifact of composition. Rather, it reinforces the point made in the discussion in Section 5.1 that leverage represents a distinct dimension of firm heterogeneity.

[31] As discussed in Section 3.4, Figure 4 has already provided descriptive evidence for parts (a) and (b) of Proposition 2, namely, that initially higher-leverage firms face steeper financing-cost curves.

Table 6: Heterogeneous Effects of Immigration from 2010 to 2019 on Firm-Level Immigrant Hiring by Initial Leverage

	Change in Immigrant Employees Relative to Initial Total Employees		
	(1)	(2)	(3)
Local immigration $dX_{r(j)}$	1.124***		1.184***
	(0.131)		(0.143)
By leverage in 2010:			
× Bottom tercile		1.184***	
		(0.143)	
× Middle tercile		1.053***	−0.131*
		(0.139)	(0.069)
× Top tercile		1.123***	−0.061
		(0.128)	(0.084)
No. commuting zones	117	117	117
No. firms	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 on firm-level immigrant hiring by initial leverage, based on the regression specified in Equation (16), instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted ethnic-enclave shift-share instrument defined in Equation (13), and interacting both $dX_{r(j)}$ and the instrument with dummies for the tercile of the 2010 leverage distribution that firm j belonged to. All columns consider as the outcome variable the change in the firm's number of immigrant employees from 2010 to 2019 relative to its total number of employees in 2010. Column (1) considers the average effect based on the version of Equation (16) without the interaction. Column (2) excludes the uninteracted terms and includes interactions for the bottom, middle, and top terciles. Column (3) includes the uninteracted terms and interactions for the middle and top terciles, so the coefficients on these interactions are differences relative to the bottom tercile. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Capital Intensity and Borrowing. I next test the first claim from part (d) of Proposition 2, which predicts that initially higher-leverage firms experience sharper declines in their capital intensity in response to the same market-level immigration shock. Figure 5 has already provided descriptive evidence that initially higher-leverage firms reduce their capital intensity by more when hiring immigrants. Insofar as they hire immigrants at the same rate as lower-leverage firms in response to the same market-level immigration shock, as suggested by Table 6, one might expect to find the same gradient in capital intensity responses by exploiting variation in local immigration shocks.

Column (1) of Table 7 repeats the estimated coefficient of -0.73, taken from column (2) of Table 5, for the average effect of immigration on firm-level capital intensity. Column (2) shows that this coefficient was -0.60, -0.73, and -0.91, respectively, for firms in the bottom, middle, and top terciles of the 2010 leverage distribution, with only the last estimate being statistically significant. However, column (3) shows that these different estimates along the initial leverage distribution are not statistically distinguishable from each other, unlike the precisely estimated but merely descriptive gradient in Figure 5.

The imprecise heterogeneity reported in column (3) of Table 7 is consistent with the fact that, relative to the other outcomes summarized in Table 3, the change in net tangible fixed assets per employee is particularly noisy, with the highest ratio of standard deviation to absolute mean. Nevertheless, the monotonic gradient reported by Table 7, and column (2)'s statistically significant estimate only for the initially highest-leverage firms, provides suggestive evidence in support of my model's prediction that immigration leads to sharper decreases in capital intensity among initially higher-leverage firms.

Table 8 provides related evidence on the heterogeneous effects of local immigration shocks on the change in firms' long-term debt. Column (1) shows that the average firm did not appear to borrow in response to immigration. However, column (2) reveals that the firms in the bottom tercile of the 2010 leverage distribution saw a sharp rise in their debt, while those in the middle and top terciles saw imprecisely estimated decreases. Column (3) further shows that the increase in the initially lowest-leverage firms' debt was statistically distinguishable from the decreases for the higher-leverage firms, unlike the gradient in capital intensity responses reported in Table 7.[32] This pattern is consistent with my model's mechanism: initially low-leverage firms, facing flatter financing-cost curves, borrowed more in response to immigration. It would also be compatible with their smaller declines in capital intensity reported in Table 7.

[32] One way to rationalize the decrease in initially higher-leverage firms' debt would be to note that the additional revenues generated by newly hired immigrants could have helped initially higher-leverage firms pay down their large existing debts. This explanation would be consistent with descriptive evidence in Appendix Figure C7 that initially high-leverage firms decreased their debt starting in 2011, at the same time as initially low-leverage firms increased theirs.

Table 7: Heterogeneous Effects of Immigration from 2010 to 2019 on Firm-Level Capital Intensity by Initial Leverage

	Change in Log Net Tangible Fixed Assets per Employee		
	(1)	(2)	(3)
Local immigration $dX_{r(j)}$	-0.732^{**}		-0.596
	(0.354)		(0.368)
By leverage in 2010:			
× Bottom tercile		-0.596	
		(0.368)	
× Middle tercile		-0.734	-0.138
		(0.472)	(0.368)
× Top tercile		-0.913^{**}	-0.317
		(0.457)	(0.462)
No. commuting zones	117	117	117
No. firms	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 on firm-level capital intensity by initial leverage, based on the regression specified in Equation (16), instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted ethnic-enclave shift-share instrument defined in Equation (13), and interacting both $dX_{r(j)}$ and the instrument with dummies for the tercile of the 2010 leverage distribution that firm j belonged to. All columns consider as the outcome variable the change in the firm's log net tangible fixed assets per employee from 2010 to 2019. Column (1) considers the average effect based on the version of Equation (16) without the interaction. Column (2) excludes the uninteracted terms and includes interactions for the bottom, middle, and top terciles. Column (3) includes the uninteracted terms and interactions for the middle and top terciles, so the coefficients on these interactions are differences relative to the bottom tercile. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Heterogeneous Effects of Immigration from 2010 to 2019 on Firm-Level Borrowing by Initial Leverage

	Symmetric Growth Rate of Long-Term Debt		
	(1)	(2)	(3)
Local immigration $dX_{r(j)}$	0.294		1.700^{***}
	(0.428)		(0.641)
By leverage in 2010:			
× Bottom tercile		1.700^{***}	
		(0.641)	
× Middle tercile		-0.647	-2.346^{***}
		(0.492)	(0.610)
× Top tercile		-0.524	-2.224^{***}
		(0.398)	(0.595)
No. commuting zones	117	117	117
No. firms	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 on firm-level borrowing by initial leverage, based on the regression specified in Equation (16), instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted ethnic-enclave shift-share instrument defined in Equation (13), and interacting both $dX_{r(j)}$ and the instrument with dummies for the tercile of the 2010 leverage distribution that firm j belonged to. All columns consider as the outcome variable the symmetric growth rate of the firm's long-term debt from 2010 to 2019. Column (1) considers the average effect based on the version of Equation (16) without the interaction. Column (2) excludes the uninteracted terms and includes interactions for the bottom, middle, and top terciles. Column (3) includes the uninteracted terms and interactions for the middle and top terciles, so the coefficients on these interactions are differences relative to the bottom tercile. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Wages and Native Employment. I finally test the second and third claims from part (d) of Proposition 2, which predict that wages and native employment fall by more at initially higher-leverage firms in response to the same market-level immigration shock. Column (1) of Table 9 repeats the estimated coefficient of -0.24, taken from column (3) of Table 5, for the average effect of immigration on firms' mean wages. Column (2) shows that this coefficient was -0.17, -0.23, and -0.33, respectively, for firms in the bottom, middle, and top terciles of the 2010 leverage distribution, with only the last estimate being statistically significant. Furthermore, column (3) shows that the estimate for the top tercile, which was nearly twice as negative as the estimate for the bottom tercile, was also statistically distinguishable from it at the 5% significance level. Thus, wages fell by more at initially higher-leverage firms, matching my model's prediction about the role of firm leverage as a moderator of immigration's wage effects.

Insofar as native labor supply is elastic to such wage losses, my model also predicts that firm leverage contributes to heterogeneity in the firm-level effects of immigration on native employment. Table 10 therefore explores this heterogeneity, benchmarking it to the average effect of -0.42 in column (1), taken from column (4) of Table 5. Column (2) shows that this negative employment effect almost doubled to -0.78 among the initially highest-leverage firms in the top tercile of the 2010 leverage distribution. In contrast, native employment declined by smaller and statistically insignificant magnitudes at the initially lower-leverage firms in the bottom and middle terciles. Column (3) confirms that the most negative estimate for the top tercile was again statistically distinguishable from the less negative estimate for the bottom tercile at the 5% significance level, so firm leverage was also an important moderator of immigration's employment effects.

The decline in mean wages documented in Table 9 would have been affected by changes in the composition of workers due both to the hiring of immigrants and to the decline in native employment. Indeed, firms hired immigrants at similar rates regardless of their initial leverage (see columns (2)-(3) of Table 6), but native employment declined more sharply at initially higher-leverage firms (see columns (2)-(3) of Table 10), which together suggest an increase in the immigrant share at those firms. Table 11 therefore reports the firm-level effects of immigration on mean native wages. Column (1) reports a weak negative effect on mean native wages at the average firm that is close to and statistically indistinguishable from zero. Although the estimates in columns (2) and (3) suggest a more negative effect at firms in the top tercile of the initial leverage distribution, this effect and its difference from the effect for firms in the bottom tercile are also imprecisely estimated. Of course, insofar as the immigrants that firms hired concentrated in lower-wage jobs (see Appendix Figure C2), these weak negative estimates could themselves reflect changes in the composition of natives: the exit of lower-wage natives would have attenuated any negative native wage effects.

Table 9: Heterogeneous Effects of Immigration from 2010 to 2019 on Firm-Level Wages by Initial Leverage

	Change in Log Mean Wage of Full-Time Employees		
	(1)	(2)	(3)
Local immigration $dX_{r(j)}$	-0.238^{*}		-0.173
	(0.133)		(0.132)
By leverage in 2010:			
× Bottom tercile		-0.173	
		(0.132)	
× Middle tercile		-0.231	-0.058
		(0.144)	(0.080)
× Top tercile		-0.334^{**}	-0.161^{**}
		(0.146)	(0.076)
No. commuting zones	117	117	117
No. firms	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 on firm-level wages by initial leverage, based on the regression specified in Equation (16), instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted ethnic-enclave shift-share instrument defined in Equation (13), and interacting both $dX_{r(j)}$ and the instrument with dummies for the tercile of the 2010 leverage distribution that firm j belonged to. All columns consider as the outcome variable the change in the log mean wage of the firm's full-time employees from 2010 to 2019. Column (1) considers the average effect based on the version of Equation (16) without the interaction. Column (2) excludes the uninteracted terms and includes interactions for the bottom, middle, and top terciles. Column (3) includes the uninteracted terms and interactions for the middle and top terciles, so the coefficients on these interactions are differences relative to the bottom tercile. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10: Heterogeneous Effects of Immigration from 2010 to 2019 on Firm-Level Native Employment by Initial Leverage

	Change in Native Employees Relative to Initial Total Employees		
	(1)	(2)	(3)
Local immigration $dX_{r(j)}$	-0.418^{**}		-0.307
	(0.166)		(0.188)
By leverage in 2010:			
$\times$ Bottom tercile		-0.307	
		(0.188)	
$\times$ Middle tercile		-0.239	0.068
		(0.188)	(0.150)
$\times$ Top tercile		-0.777^{***}	-0.470^{**}
		(0.215)	(0.197)
No. commuting zones	117	117	117
No. firms	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 on firm-level native employment by initial leverage, based on the regression specified in Equation (16), instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted ethnic-enclave shift-share instrument defined in Equation (13), and interacting both $dX_{r(j)}$ and the instrument with dummies for the tercile of the 2010 leverage distribution that firm j belonged to. All columns consider as the outcome variable the change in the firm's number of native employees from 2010 to 2019 relative to its total number of employees in 2010. Column (1) considers the average effect based on the version of Equation (16) without the interaction. Column (2) excludes the uninteracted terms and includes interactions for the bottom, middle, and top terciles. Column (3) includes the uninteracted terms and interactions for the middle and top terciles, so the coefficients on these interactions are differences relative to the bottom tercile. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11: Heterogeneous Effects of Immigration from 2010 to 2019 on Firm-Level Native Wages by Initial Leverage

	Change in Log Mean Wage of Native Full-Time Employees		
	(1)	(2)	(3)
Local immigration $dX_{r(j)}$	−0.041		−0.020
	(0.124)		(0.125)
By leverage in 2010:			
× Bottom tercile		−0.020	
		(0.125)	
× Middle tercile		−0.014	−0.007
		(0.136)	(0.081)
× Top tercile		−0.100	−0.080
		(0.136)	(0.076)
No. commuting zones	117	117	117
No. firms	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 on firm-level native wages by initial leverage, based on the regression specified in Equation (16), instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted ethnic-enclave shift-share instrument defined in Equation (13), and interacting both $dX_{r(j)}$ and the instrument with dummies for the tercile of the 2010 leverage distribution that firm j belonged to. All columns consider as the outcome variable the change in the log mean wage of the firm's native full-time employees from 2010 to 2019. Column (1) considers the average effect based on the version of Equation (16) without the interaction. Column (2) excludes the uninteracted terms and includes interactions for the bottom, middle, and top terciles. Column (3) includes the uninteracted terms and interactions for the middle and top terciles, so the coefficients on these interactions are differences relative to the bottom tercile. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 12: Heterogeneous Effects of Immigration from 2010 to 2019 on Firm-Level Native Wages by Initial Leverage—Alternative Reweighting

	Change in Log Mean Wage of Native Full-Time Employees		
	(1)	(2)	(3)
Local immigration $dX_{r(j)}$	-0.189^{*}		-0.134
	(0.106)		(0.105)
By leverage in 2010:			
× Bottom tercile		-0.134	
		(0.105)	
× Middle tercile		-0.185	-0.051
		(0.113)	(0.074)
× Top tercile		-0.267^{**}	-0.132^{*}
		(0.124)	(0.073)
No. commuting zones	117	117	117
No. firms	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 on firm-level native wages by initial leverage, based on the regression specified in Equation (16), instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted share instrument defined in Equation (15), and interacting both $dX_{r(j)}$ and the instrument with dummies for the tercile of the 2010 leverage distribution that firm j belonged to. All columns consider as the outcome variable the change in the log mean wage of the firm's native full-time employees from 2010 to 2019. Column (1) considers the average effect based on the version of Equation (16) without the interaction. Column (2) excludes the uninteracted terms and includes interactions for the bottom, middle, and top terciles. Column (3) includes the uninteracted terms and interactions for the middle and top terciles, so the coefficients on these interactions are differences relative to the bottom tercile. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

To further probe the weak negative native wage effects presented in Table 11, which were based on instrumenting the local inflows of immigrants with the reweighted ethnic-enclave shift-share instrument defined in Equation (13), Table 12 presents estimates based on the alternatively reweighted instrument defined in Equation (15).[33] Relative to Table 11, Table 12 presents stronger evidence that the effect of immigration on mean native wages was negative on average, and that it was more negative at initially higher-leverage firms. Reassuringly, Appendix Tables E5-E10 show that the patterns documented in Tables 5-10 broadly hold for this alternatively reweighted instrument.

Taken together, the results in Tables 6–12 provide internally consistent evidence for the key point that this paper has made, namely, that capital-market frictions are an important and largely overlooked mechanism in the ongoing debates on immigration's effects. As Table 6 shows, even with large existing debt burdens, firms can and do afford to hire newly arriving immigrants in response to an immigration-induced increase in local labor supply. Yet, they may not be able to afford to adjust their capital stocks if their high initial leverage makes additional borrowing too expensive; the estimates in Tables 7 and 8 are suggestive of the relevance of this mechanism, albeit imprecisely.

Finally, Tables 9–12 demonstrate that a firm's initial leverage has important implications for the effects of the local immigration shock on its workers. Specifically, wages and native employment fell by more among the firms with higher initial leverage, which my results suggest may have been due to these firms increasing their borrowing by less and therefore experiencing sharper declines in their capital intensity.

Other Dimensions of Firm Heterogeneity. Of course, a firm's initial leverage is not the only characteristic that may shape its response to a market-level immigration shock. As discussed above, Appendix Tables E1–E4 show that firms in low-skill sectors, younger firms, smaller firms, and less skill-intensive firms hired newly arriving immigrants at higher rates than other firms. Appendix Tables E11–E14 therefore extend this analysis to capital intensity, borrowing, mean wages, and native employment, estimating separate effects of immigration for different categories of firms along each of these four dimensions of firm heterogeneity: sector category, age, size, and skill intensity.

Two patterns stand out. First, firm age and size, both often used as proxies for financial constraints (Hadlock and Pierce, 2010), shaped firms' responses in a way that resembles leverage. Appendix Table E12 shows that firms founded after 2000 did not borrow more in response to local immigration, even though they hired newly arriving immigrants at higher rates than older firms (see Appendix Table E2). Their capital intensity and mean

[33] The latter instrument ignores the origin country-specific shifts when weighting the origin country-specific shares. See Section 4.2 for a further discussion of the differences between the two instruments.

wages also fell by 15% and 4.2%, respectively, in response to a 10-percentage-point increase in local immigrant employment relative to initial total employment. In contrast, firms founded in or before 1995 increased their borrowing, and their capital intensity, wages, and native employment fell by less. Firm size points in a similar direction: Appendix Table E13 shows that firms in the top tercile of the 2010 size distribution increased their borrowing by more than those in the bottom tercile, which experienced the largest declines in both capital intensity and native employment.[34]

Second, Appendix Tables E11 and E14 show that capital intensity fell most sharply among firms in high-skill sectors and among firms in the top tercile of the 2010 skill intensity distribution. For skill-intensive firms, this decline coincided with a more negative effect on mean wages but a less negative effect on native employment than for the least skill-intensive firms. One interpretation of this result is that skill-intensive firms, whose workers are less substitutable with newly arriving immigrants, adjusted to the decline in their capital intensity more through wages than through employment.

Nevertheless, given any of these other dimensions of firm heterogeneity, higher initial leverage may still constrain firms' responses to a market-level immigration shock. Appendix Tables E15–E19 therefore report the estimated effects of immigration separately for each combination of a firm's tercile in the 2010 leverage distribution and its category along each of the four other dimensions. Appendix Table E15 first applies this approach to immigrant hiring. Within each of these other dimensions, across whose categories immigrant hiring did differ, initial leverage did not impair hiring: the differences between the top and bottom leverage terciles were never statistically significantly negative.

The remaining results, reported in Appendix Tables E16–E19, are consistent with those for all firms in Tables 7–10. The difference in the effect on capital intensity between the top and bottom leverage terciles is negative in 9 of the 12 categories, but, as in Table 7, these differences are imprecisely estimated and not statistically significant. In contrast, the difference in the effect on borrowing is negative in 11 of the 12 categories and statistically significant in 9. Likewise, the differences in the effects on mean wages (native employment) are also negative in 9 (10) of the 12 categories and statistically significant in 5 (4) of them. Taken together, these results suggest that initial leverage represents a dimension of heterogeneity in firms' responses to immigration that is distinct from their sector, age, size, and skill intensity: within each of these dimensions, initially higher-leverage firms hired immigrants at similar rates as their less leveraged counterparts but borrowed less, with costly consequences for their workers.

[34] Although immigration's effects on mean wages did not differ much along the 2010 firm size distribution, this could simply reflect heterogeneous composition effects arising from the heterogeneous effects on both immigrant hiring (Appendix Table E3) and native employment (Appendix Table E13).

6 Conclusion

Whether an economy can absorb an increase in labor supply without harming incumbent workers depends on whether firms can expand their capital stocks alongside their workforces. This paper argues that, because investment must be financed, this adjustment is constrained by firms' access to credit, and that firms' existing debt burdens are a key determinant of that access. Germany's experience during the 2010s, when a large immigration shock coincided with a sharp decline in firms' capital intensity, provides a setting in which this channel can be observed. The evidence points consistently in the same direction: firms hired immigrants regardless of their financial condition, but only those with room to borrow took on more debt in response, allowing their capital stocks to keep closer pace. As a result, the costs of immigration for native workers were concentrated at firms whose high initial leverage left them unable to scale up.

These findings suggest that the consequences of immigration for native workers depend on the financial condition of the firms that employ them. One implication is that the same immigration shock may have different effects depending on when it arrives: an economy whose firms are deleveraging, as many European firms were following the global financial crisis and the sovereign debt crisis, may be less able to expand its capital stock in response to an increase in labor supply. Another implication is that policies easing access to credit for highly indebted but otherwise viable firms could complement immigration policy, helping capital keep pace with labor and mitigating native workers' losses. More generally, the results suggest that corporate balance sheets belong alongside skill composition, technology adoption, and firm entry among the margins that determine how local economies absorb labor supply shocks.

Several directions for future research follow. First, while this paper focuses on firms' intensive-margin responses, a natural extension would be to examine whether high leverage also shapes the extensive margin, for instance by affecting which firms exit or enter in response to immigration. Second, quantifying the aggregate implications of the mechanism, such as the share of the decline in Germany's capital-labor ratio during the 2010s attributable to credit constraints, would require embedding the firm-level estimates in a general equilibrium framework. Third, the mechanism is not specific to immigration: the same capital-market frictions may shape how firms respond to other labor supply shocks, such as demographic change or shifts in labor force participation, and to labor demand shocks that require complementary investment. Finally, exploiting settings with exogenous variation in credit supply, such as lender-specific shocks, alongside immigration shocks would help distinguish the role of leverage itself from that of other characteristics correlated with it.

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Appendix A: Model

In this appendix, I prove the propositions stated in Section 2. Section A.1 presents the proof of Proposition 1. Section A.2 presents the proof of Proposition 2.

A.1 Proof of Proposition 1

I first derive firm j's responses to the market-level immigration shock dI, then prove part (b) of Proposition 1 for capital intensity and wages, next prove part (b) for native employment, and finally prove part (a) for immigrant employment.[35]

Firm-Level Responses. The first-order conditions of the firms' optimization problem are:

$$A_j F_K(K_j, L_j) = \alpha A_j K_j^{\alpha-1} L_j^{1-\alpha} = \rho_j(K_j) + \rho_j'(K_j) K_j = (1+\lambda_j)\rho_j(K_j) \tag{A1}$$

$$A_j F_L(K_j, L_j) = (1-\alpha) A_j K_j^{\alpha} L_j^{-\alpha} = w(L_j) + w'(L_j) L_j = \left(1 + \frac{1}{\beta}\right) w(L_j) \tag{A2}$$

where the last equality in Equation (A1) follows from the constant elasticity λ_j of $\rho_j(K_j)$ defined in Section 2.1, and the last equality in Equation (A2) follows from the constant elasticity β of firm j's labor supply also defined in Section 2.1.

Insert the expression for $\rho_j(K_j)$ into Equation (A1), take the resulting expression's natural logarithm, and totally differentiate it holding α, A_j, $\underline{\rho}_j$, and λ_j fixed:

$$(\alpha - 1)(d \ln K_j - d \ln L_j) = \lambda_j \, d \ln K_j$$

$$\implies \frac{d \ln \left(\frac{K_j}{L_j}\right)}{d \ln L_j} = \frac{-\lambda_j}{1 - \alpha + \lambda_j} \tag{A3}$$

Likewise, take the natural logarithm of Equation (A2), totally differentiate it holding α, A_j, and β fixed, and insert Equation (A3) into it:

$$\alpha \, d \ln \left(\frac{K_j}{L_j}\right) = d \ln w_j$$

$$\implies \frac{d \ln w_j}{d \ln L_j} = \frac{-\alpha \lambda_j}{1 - \alpha + \lambda_j} \tag{A4}$$

[35] For simplicity of notation, I omit the subscript 0 denoting initial equilibrium values throughout this proof. All levels and shares, such as $\bar{L}^{imm}/\bar{L}$ and L_j/L, refer to their initial values.

where $w_j = w(L_j)$. Equations (A3) and (A4) describe how firm j's capital intensity K_j/L_j and wage w_j, respectively, respond to an increase in its number of employees L_j. Now consider that the firm's labor supply condition implies:

$$d \ln L_j = d \ln \left(\frac{\bar{L}}{\sum_{j' \in \mathcal{J}} w_{j'}^{\beta}} \right) + \beta \, d \ln w_j \tag{A5}$$

where, since each firm is small relative to the labor market, firm j takes the aggregate term $\bar{L} / \sum_{j' \in \mathcal{J}} w_{j'}^{\beta}$ as given. Insert Equation (A4) into Equation (A5) and solve for $d \ln L_j$:

$$\frac{d \ln L_j}{d \ln \left(\frac{\bar{L}}{\sum_{j' \in \mathcal{J}} w_{j'}^{\beta}} \right)} = \frac{1 - \alpha + \lambda_j}{1 - \alpha + \lambda_j (1 + \alpha \beta)} \tag{A6}$$

Multiplying Equations (A3) and (A4) by Equation (A6) then yields:

$$\frac{d \ln \left(\frac{K_j}{L_j} \right)}{d \ln \left(\frac{\bar{L}}{\sum_{j' \in \mathcal{J}} w_{j'}^{\beta}} \right)} = \frac{-\lambda_j}{1 - \alpha + \lambda_j (1 + \alpha \beta)} \tag{A7}$$

$$\frac{d \ln w_j}{d \ln \left(\frac{\bar{L}}{\sum_{j' \in \mathcal{J}} w_{j'}^{\beta}} \right)} = \frac{-\alpha \lambda_j}{1 - \alpha + \lambda_j (1 + \alpha \beta)} \tag{A8}$$

Next, rewrite $d \ln \left[\bar{L} / \sum_{j' \in \mathcal{J}} w_{j'}^{\beta} \right]$ in terms of the immigration shock dI. Since the native population is fixed, $dI = d\bar{L}^{imm} / \bar{L} = d \ln \bar{L}$. Since the outside option's wage w_b is fixed, only firms $j' \in \mathcal{J} \setminus \{b\}$ contribute to the change in $\sum_{j' \in \mathcal{J}} w_{j'}^{\beta}$. Using $w_{j'}^{\beta} / \sum_{j'' \in \mathcal{J}} w_{j''}^{\beta} = L_{j'} / \bar{L}$ and inserting Equation (A8):

$$d \ln \left(\frac{\bar{L}}{\sum_{j' \in \mathcal{J}} w_{j'}^{\beta}} \right) = d \ln \bar{L} - \frac{\beta \sum_{j' \in \mathcal{J} \setminus \{b\}} w_{j'}^{\beta} \, d \ln w_{j'}}{\sum_{j' \in \mathcal{J}} w_{j'}^{\beta}}$$

$$\implies d \ln \left(\frac{\bar{L}}{\sum_{j' \in \mathcal{J}} w_{j'}^{\beta}} \right) = dI + \left[\beta \frac{L}{\bar{L}} \sum_{j' \in \mathcal{J} \setminus \{b\}} \left(\frac{L_{j'}}{L} \times \frac{\alpha \lambda_{j'}}{1 - \alpha + \lambda_{j'} (1 + \alpha \beta)} \right) \right] d \ln \left(\frac{\bar{L}}{\sum_{j' \in \mathcal{J}} w_{j'}^{\beta}} \right)$$

$$\implies d \ln \left(\frac{\bar{L}}{\sum_{j' \in \mathcal{J}} w_{j'}^{\beta}} \right) = \frac{dI}{1 - \beta \frac{L}{\bar{L}} \sum_{j' \in \mathcal{J} \setminus \{b\}} \left(\frac{L_{j'}}{L} \times \frac{\alpha \lambda_{j'}}{1 - \alpha + \lambda_{j'} (1 + \alpha \beta)} \right)} \equiv \frac{dI}{C} \tag{A9}$$

where the term C in the denominator of Equation (A9) depends on the labor supply elasticity β, the share $L/\bar{L}$ of workers who are employed by firms rather than selecting the outside option, and the employment share $L_{j'}/L$-weighted average of firms' wage elasticities from Equation (A8). Importantly, C is not firm-specific. Moreover, since $1-\alpha > 0$, the magnitude of each firm's wage elasticity satisfies:

$$\frac{\alpha\lambda_{j'}}{[1-\alpha+\lambda_{j'}(1+\alpha\beta)]} < \alpha/(1+\alpha\beta)$$

and since $L/\bar{L} \leq 1$:

$$C > 1 - \frac{\alpha\beta}{1+\alpha\beta} = \frac{1}{1+\alpha\beta} > 0.$$

Part (b): Capital Intensity and Wages. Combining Equations (A7)–(A9):

$$\frac{d\ln\left(\frac{K_j}{L_j}\right)}{dI} = \frac{1}{C} \times \frac{-\lambda_j}{1-\alpha+\lambda_j(1+\alpha\beta)} \tag{A10}$$

$$\frac{d\ln w_j}{dI} = \frac{1}{C} \times \frac{-\alpha\lambda_j}{1-\alpha+\lambda_j(1+\alpha\beta)} \tag{A11}$$

Both expressions are strictly decreasing in λ_j, since:

$$\frac{\partial}{\partial\lambda_j}\left[\frac{-\lambda_j}{1-\alpha+\lambda_j(1+\alpha\beta)}\right] = \frac{-(1-\alpha)}{\left[1-\alpha+\lambda_j(1+\alpha\beta)\right]^2} < 0,$$

the corresponding derivative for Equation (A11) is the same expression scaled by $\alpha > 0$, and $C > 0$ is common to all firms. Thus, firms with higher λ_j experience more negative proportional changes in their capital intensity and wages in response to immigration.

Part (b): Total and Native Employment. Combining Equations (A6) and (A9), firm j's total employment responds to the immigration shock according to:

$$\frac{d\ln L_j}{dI} = \frac{1}{C} \times \frac{1-\alpha+\lambda_j}{1-\alpha+\lambda_j(1+\alpha\beta)} \tag{A12}$$

Since:

$$\frac{\partial}{\partial\lambda_j}\left[\frac{1-\alpha+\lambda_j}{1-\alpha+\lambda_j(1+\alpha\beta)}\right] = \frac{-\alpha\beta(1-\alpha)}{\left[1-\alpha+\lambda_j(1+\alpha\beta)\right]^2} < 0$$

and $C > 0$ is common to all firms, Equation (A12) is strictly decreasing in λ_j.

Given $p_j = w_j^\beta / \sum_{j' \in \mathcal{J}} w_{j'}^\beta$, firm j's total employment, native employment, and immigrant employment are $L_j = p_j \bar{L}$, $L_j^{nat} = p_j \bar{L}^{nat}$, and $L_j^{imm} = p_j \bar{L}^{imm}$, respectively. Since $d \ln p_j = d \ln L_j - dI$ and the native population $\bar{L}^{nat}$ is fixed, the change in firm j's native employment relative to its initial total employment is:

$$dL_j^{nat} = \bar{L}^{nat} \, dp_j$$

$$\implies \frac{dL_j^{nat}}{L_j} = \frac{\bar{L}^{nat} \, dp_j}{p_j \bar{L}} = \frac{\bar{L}^{nat}}{\bar{L}} \, d \ln p_j$$

$$\implies \frac{dL_j^{nat} / L_j}{dI} = \frac{\bar{L}^{nat}}{\bar{L}} \left(\frac{d \ln L_j}{dI} - 1 \right) \tag{A13}$$

Since $\bar{L}^{nat} / \bar{L} > 0$, Equation (A13) inherits the gradient of Equation (A12) and is therefore strictly decreasing in λ_j. Thus, firms with higher λ_j also experience more negative changes in their native employment, completing the proof of part (b) of Proposition 1.

Part (a): Immigrant Employment. The change in firm j's immigrant employment relative to its initial total employment is:

$$dL_j^{imm} = p_j \, d\bar{L}^{imm} + \bar{L}^{imm} \, dp_j$$

$$\implies \frac{dL_j^{imm}}{L_j} = \frac{p_j \, d\bar{L}^{imm}}{p_j \bar{L}} + \frac{\bar{L}^{imm} \, dp_j}{p_j \bar{L}} = dI + \frac{\bar{L}^{imm}}{\bar{L}} \, d \ln p_j$$

$$\implies \frac{dL_j^{imm} / L_j}{dI} = 1 + \frac{\bar{L}^{imm}}{\bar{L}} \left(\frac{d \ln L_j}{dI} - 1 \right) \tag{A14}$$

Comparing Equations (A13) and (A14), the gradient of firm j's immigrant employment response with respect to λ_j is $\bar{L}^{imm} / \bar{L}^{nat}$ times that of its native employment response. If $\bar{L}^{imm} / \bar{L} \approx 0$, then Equation (A14) implies:

$$\frac{dL_j^{imm} / L_j}{dI} \approx 1$$

for all firms j, regardless of λ_j, proving part (a) of Proposition 1. Intuitively, immigrant and native workers have identical preferences over firms and therefore sort across firms identically: both groups' employment at firm j is proportional to its share p_j of the labor market. Every firm's employment of immigrants rises with the immigration shock in proportion to its initial share, contributing the term 1 in Equation (A14). Firms

differ only in how their share p_j changes, which depends on how their wages respond. Since firms with higher λ_j do not expand their capital stocks by as much, their wages fall by more, so they lose workers to nonemployment or to other firms. This loss of market share reduces their employment of immigrants and natives alike, in proportion to each group's share of the labor market. When immigrants initially make up only a small share of the labor market, this adjustment therefore falls almost entirely on native employment relative to total employment, while firms' hiring of immigrants is approximately uniform across firms.

A.2 Proof of Proposition 2

I first derive firm j's labor demand and net-of-wages profit given its capital stock and productivity shock, then characterize the optimal financial contract following Bernanke et al. (1999), next prove part (a) of Proposition 2 for the convexity of log financing cost in log leverage, use the elasticity derived in part (a) to prove part (b) for the steepness λ_j of firm j's financing-cost curve, and finally prove parts (c) and (d) for the effect of a market-level immigration shock dI on immigrant employment, capital intensity, wages, and native employment by applying Proposition 1.[36]

Labor Demand. Firm j chooses capital K_j before observing its shock ω_j and chooses labor L_j after observing ω_j. Firm j therefore chooses L_j to maximize net-of-wages profits given K_j, ω_j, its production $A_j F(K_j, L_j)$, and its labor-cost curve $w(L_j)$:

$$\Pi(\omega_j, K_j) \equiv \max_{L_j} \{\omega_j A_j F(K_j, L_j) - w(L_j)L_j\} = \max_{L_j} \left\{\omega_j A_j K_j^{\alpha} L_j^{1-\alpha} - W L_j^{1+\frac{1}{\beta}}\right\} \quad \text{(A15)}$$

where $W \equiv \left(\sum_{j' \in \mathcal{J}} w_{j'}^{\beta} / \bar{L}\right)^{1/\beta}$, so that firm j's labor supply condition from Section 2.1 implies $w(L_j) = W L_j^{1/\beta}$. Since each firm is small relative to the labor market, firm j takes W as given. The first-order condition of Equation (A15) is:

$$\omega_j A_j F_L(K_j, L_j) = (1-\alpha)\,\omega_j A_j K_j^{\alpha} L_j^{-\alpha} = w(L_j) + w'(L_j)L_j = \left(1 + \frac{1}{\beta}\right) W L_j^{\frac{1}{\beta}} \quad \text{(A16)}$$

where the last equality follows from the constant elasticity β of firm j's labor supply. Equation (A16) is Equation (A2) with $\omega_j A_j$ in place of A_j. Solve Equation (A16) for L_j:

$$L_j = \left[\frac{\beta(1-\alpha)}{(1+\beta)W}\,\omega_j A_j K_j^{\alpha}\right]^{\frac{\beta}{1+\alpha\beta}} \quad \text{(A17)}$$

[36] For simplicity of notation, I omit the subscript 0 denoting initial equilibrium values throughout this proof, as in Appendix A.1. To avoid overlap with the notation of Section 2.1, I denote the Lagrange multiplier on the lender's participation constraint by Λ rather than λ.

Net-of-Wages Profits. Multiply both sides of Equation (A16) by L_j and rearrange terms to express firm j's wage bill $w(L_j)L_j$ as a constant share of its output $\omega_j A_j F(K_j, L_j)$:

$$WL_j^{1+\frac{1}{\beta}} = \frac{\beta(1-\alpha)}{1+\beta}\,\omega_j A_j K_j^{\alpha} L_j^{1-\alpha}$$

Insert this expression into Equation (A15):

$$\Pi(\omega_j, K_j) = \left[1 - \frac{\beta(1-\alpha)}{1+\beta}\right]\omega_j A_j K_j^{\alpha} L_j^{1-\alpha}$$

Then, into this resulting expression, insert Equation (A17):

$$\Pi(\omega_j, K_j) = \frac{1+\alpha\beta}{1+\beta}\,\omega_j A_j K_j^{\alpha}\left[\frac{\beta(1-\alpha)}{(1+\beta)W}\,\omega_j A_j K_j^{\alpha}\right]^{\frac{\beta(1-\alpha)}{1+\alpha\beta}}$$

$$\implies \Pi(\omega_j, K_j) = \omega_j^{\theta}\,\Phi_j K_j^{\alpha\theta} \tag{A18}$$

where:

$$\theta \equiv \frac{1+\beta}{1+\alpha\beta} \qquad \text{and} \qquad \Phi_j \equiv \frac{1+\alpha\beta}{1+\beta}\,A_j^{\theta}\left[\frac{\beta(1-\alpha)}{(1+\beta)W}\right]^{\theta-1}$$

The last exponent in the second expression uses $\theta - 1 = \beta(1-\alpha)/(1+\alpha\beta)$. Together, $\alpha \in (0,1)$ and $\beta \in (0,\infty)$ imply $\alpha\theta = \alpha(1+\beta)/(1+\alpha\beta) < 1$. Thus, Equation (A18) implies that firm j's net-of-wages profits are strictly concave in its capital K_j.

Finally, define $x_j \equiv \omega_j^{\theta}$ and normalize $E[x_j] = 1$, which is without loss of generality since $E[\omega_j^{\theta}]$ can be absorbed into A_j. Equation (A18) then becomes $\Pi(\omega_j, K_j) = x_j \Phi_j K_j^{\alpha\theta}$, with expected value $\Phi_j K_j^{\alpha\theta}$.[37] Since $\alpha\theta < 1$, firm j's expected marginal return to capital, $\alpha\theta\Phi_j K_j^{\alpha\theta-1}$, is strictly decreasing in K_j. This represents the key difference from Bernanke et al. (1999), where the return to capital is constant: firms' monopsony power over workers in labor markets (unless $\beta \to \infty$) results in decreasing returns to capital.

Optimal Financial Contract. As described in Section 2.2, firm j finances its capital stock with its net worth N_j and debt $D_j = K_j - N_j$, pays its workers before its lenders, and in default forfeits its net-of-wages profits, of which lenders lose a share $\mu \in (0,1)$ to verification. Following Bernanke et al. (1999), the optimal contract is then standard risky debt, with firm j defaulting if and only if x_j falls below the cutoff $\bar{x}_j$ defined by:

[37] The term $x_j \Phi_j K_j^{\alpha\theta}$ plays the role of $\omega R^k Q K$ in Bernanke et al. (1999).

$$\bar{x}_j \Phi_j K_j^{\alpha\theta} = (1 + r_j)(K_j - N_j) \tag{A19}$$

where r_j is the net interest rate paid by firm j when it does not default. If $x_j \geq \bar{x}_j$, firm j repays $\bar{x}_j \Phi_j K_j^{\alpha\theta}$ and keeps $(x_j - \bar{x}_j)\Phi_j K_j^{\alpha\theta}$. If $x_j < \bar{x}_j$, firm j receives nothing, and the lender pays $\mu x_j \Phi_j K_j^{\alpha\theta}$ to verify x_j and keeps $(1-\mu)x_j \Phi_j K_j^{\alpha\theta}$. Equation (A19) implies that, given K_j, choosing $\bar{x}_j$ is equivalent to choosing r_j.

Lenders observe firm j's total factor productivity A_j, net worth N_j, and capital stock K_j but observe its shock ω_j only by paying the verification cost. Since x_j is independent across firms, each lender's portfolio is riskless, and competition among lenders drives the expected return on each loan to $1 + \underline{r}$:

$$\left[\bar{x}_j \Pr(x_j \geq \bar{x}_j) + (1-\mu)\, E(x_j \mid x_j < \bar{x}_j) \Pr(x_j < \bar{x}_j)\right] \Phi_j K_j^{\alpha\theta} = (1 + \underline{r})(K_j - N_j) \tag{A20}$$

Further characterizing Equation (A20) requires characterizing $\Pr(x_j \geq \bar{x}_j)$, so let F and f denote the cumulative distribution and probability density functions of x_j. As in Bernanke et al. (1999), define the lender's expected gross share of firm j's net-of-wages profits, $\Gamma(\bar{x}_j)$, and the expected verification costs as a share of those profits, $\mu G(\bar{x}_j)$:

$$\Gamma(\bar{x}_j) \equiv \int_0^{\bar{x}_j} x f(x)\, dx + \bar{x}_j \left[1 - F(\bar{x}_j)\right] \qquad \text{and} \qquad \mu G(\bar{x}_j) \equiv \mu \int_0^{\bar{x}_j} x f(x)\, dx \tag{A21}$$

The first term of $\Gamma(\bar{x}_j)$ is the lender's expected receipts in default, before verification costs, and the second term is its expected receipts when firm j repays in full, so that $1 - \Gamma(\bar{x}_j)$ is firm j's expected share. $\mu G(\bar{x}_j)$ is the share of firm j's expected net-of-wages profits that is lost to verification in default, which neither the lender nor firm j receives. The lender's expected net share is therefore $\Gamma(\bar{x}_j) - \mu G(\bar{x}_j)$. Since $\bar{x}_j \Pr(x_j \geq \bar{x}_j) = \bar{x}_j[1 - F(\bar{x}_j)]$ and $E(x_j \mid x_j < \bar{x}_j) \Pr(x_j < \bar{x}_j) = G(\bar{x}_j)$, rewrite Equation (A20) as:

$$\left[\Gamma(\bar{x}_j) - \mu G(\bar{x}_j)\right] \Phi_j K_j^{\alpha\theta} = (1 + \underline{r})(K_j - N_j) \tag{A22}$$

Differentiating Equation (A21) yields:

$$\Gamma'(\bar{x}_j) = 1 - F(\bar{x}_j) > 0, \qquad \Gamma''(\bar{x}_j) = -f(\bar{x}_j) < 0, \qquad \mu G'(\bar{x}_j) = \mu \bar{x}_j f(\bar{x}_j) > 0$$

Thus, raising the cutoff increases the lender's expected gross share at a decreasing rate, while also increasing expected verification costs. Since $E[x_j] = 1$, firm j's expected share is $1 - \Gamma(\bar{x}_j) = \int_{\bar{x}_j}^{\infty} (x - \bar{x}_j) f(x)\, dx$, so that $0 < \Gamma(\bar{x}_j) < 1$. Moreover, the lender's expected net share, $\Gamma(\bar{x}_j) - \mu G(\bar{x}_j) = \bar{x}_j[1 - F(\bar{x}_j)] + (1-\mu)G(\bar{x}_j)$, is strictly positive, and it converges to 0 as $\bar{x}_j \to 0$ and to $1 - \mu$ as $\bar{x}_j \to \infty$.

Regularity. I assume that $\ln \omega_j$ is normally distributed, so that $\ln x_j = \theta \ln \omega_j$ is normally distributed, with standard deviation $\sigma \equiv \theta \sigma_\omega$. As Bernanke et al. (1999) show, x_j then satisfies their regularity condition that $\bar{x}_j h(\bar{x}_j)$ is strictly increasing, where $h(\bar{x}_j) \equiv f(\bar{x}_j)/[1 - F(\bar{x}_j)]$ denotes the hazard rate of x_j. This condition has two implications. First, factoring $1 - F(\bar{x}_j)$ out of the derivative of the lender's expected net share yields:

$$\Gamma'(\bar{x}_j) - \mu G'(\bar{x}_j) = \left[1 - F(\bar{x}_j)\right] \left[1 - \mu \bar{x}_j h(\bar{x}_j)\right]$$

Since $\bar{x}_j h(\bar{x}_j)$ is strictly increasing, from 0 as $\bar{x}_j \to 0$ to ∞ as $\bar{x}_j \to \infty$, there exists a unique $\bar{x}^*$ that solves $\mu \bar{x}^* h(\bar{x}^*) = 1$, such that:

$$\Gamma'(\bar{x}_j) - \mu G'(\bar{x}_j) \begin{array}{c} > \\ = \\ < \end{array} 0 \quad \text{for} \quad \bar{x}_j \begin{array}{c} < \\ = \\ > \end{array} \bar{x}^* \tag{A23}$$

Thus, the lender's expected net share reaches a maximum at $\bar{x}^*$. Second, use $\Gamma'(\bar{x}_j) = 1 - F(\bar{x}_j)$, $\Gamma''(\bar{x}_j) = -f(\bar{x}_j)$, $G'(\bar{x}_j) = \bar{x}_j f(\bar{x}_j)$, and $G''(\bar{x}_j) = f(\bar{x}_j) + \bar{x}_j f'(\bar{x}_j)$ to write:

$$\Gamma'(\bar{x}_j) G''(\bar{x}_j) - \Gamma''(\bar{x}_j) G'(\bar{x}_j) = \left[1 - F(\bar{x}_j)\right] \left[f(\bar{x}_j) + \bar{x}_j f'(\bar{x}_j)\right] + \bar{x}_j f(\bar{x}_j)^2$$

Differentiate $\bar{x}_j h(\bar{x}_j)$ using $h'(\bar{x}_j) = \left\{f'(\bar{x}_j)\left[1 - F(\bar{x}_j)\right] + f(\bar{x}_j)^2\right\} / \left[1 - F(\bar{x}_j)\right]^2$:

$$\frac{\partial \left(\bar{x}_j h(\bar{x}_j)\right)}{\partial \bar{x}_j} = h(\bar{x}_j) + \bar{x}_j h'(\bar{x}_j)$$

$$\implies \frac{\partial \left(\bar{x}_j h(\bar{x}_j)\right)}{\partial \bar{x}_j} = \frac{f(\bar{x}_j)\left[1 - F(\bar{x}_j)\right] + \bar{x}_j f'(\bar{x}_j)\left[1 - F(\bar{x}_j)\right] + \bar{x}_j f(\bar{x}_j)^2}{\left[1 - F(\bar{x}_j)\right]^2} > 0$$

where the inequality follows from the regularity condition. The numerator of this last expression is the right-hand side of the previous one, so:

$$\Gamma'(\bar{x}_j) G''(\bar{x}_j) - \Gamma''(\bar{x}_j) G'(\bar{x}_j) = \frac{\partial \left(\bar{x}_j h(\bar{x}_j)\right)}{\partial \bar{x}_j} \left[1 - F(\bar{x}_j)\right]^2 > 0 \tag{A24}$$

Equation (A23) implies that the optimal contract never sets a cutoff above $\bar{x}^*$, since a lower cutoff would deliver the lender the same expected net share while leaving firm j a larger expected share $1 - \Gamma(\bar{x}_j)$. I therefore restrict attention to $\bar{x}_j \in (0, \bar{x}^*)$. Equation (A24) will sign the derivatives of the first-order conditions of firm j's problem below.

Capital Demand. Before observing its shock ω_j, and anticipating both its ex-post labor choice in Equation (A17) and the contract's terms in default, firm j takes Φ_j, N_j, and $\underline{r}$ as given and chooses its capital stock K_j and cutoff $\bar{x}_j$ to maximize its expected share of net-of-wages profits, subject to the lender's participation constraint in Equation (A22):

$$\max_{K_j,\,\bar{x}_j} \left[1-\Gamma(\bar{x}_j)\right]\Phi_j K_j^{\alpha\theta} \quad \text{s.t.} \quad \left[\Gamma(\bar{x}_j)-\mu G(\bar{x}_j)\right]\Phi_j K_j^{\alpha\theta} = (1+\underline{r})(K_j-N_j) \tag{A25}$$

The Lagrangian of Equation (A25) is:

$$\mathcal{L}_j = \left[1-\Gamma(\bar{x}_j)\right]\Phi_j K_j^{\alpha\theta} + \Lambda_j\left\{\left[\Gamma(\bar{x}_j)-\mu G(\bar{x}_j)\right]\Phi_j K_j^{\alpha\theta} - (1+\underline{r})(K_j-N_j)\right\} \tag{A26}$$

The first-order conditions for the solution $\bar{x}_j \in (0, \bar{x}^*)$ implied by Equation (A23) are:

$$\bar{x}_j: \quad -\Gamma'(\bar{x}_j) + \Lambda_j\left[\Gamma'(\bar{x}_j) - \mu G'(\bar{x}_j)\right] = 0 \tag{A27}$$

$$K_j: \quad \alpha\theta\Phi_j K_j^{\alpha\theta-1}\left\{\left[1-\Gamma(\bar{x}_j)\right] + \Lambda_j\left[\Gamma(\bar{x}_j)-\mu G(\bar{x}_j)\right]\right\} - \Lambda_j(1+\underline{r}) = 0 \tag{A28}$$

together with the participation constraint in Equation (A22). Solve Equation (A27) for the Lagrange multiplier as a function of the cutoff:

$$\Lambda(\bar{x}_j) = \frac{\Gamma'(\bar{x}_j)}{\Gamma'(\bar{x}_j) - \mu G'(\bar{x}_j)} \tag{A29}$$

The multiplier $\Lambda(\bar{x}_j)$ is firm j's shadow cost of promising its lender an additional unit of expected return. As shown below, this shadow cost determines how firm j's financing cost varies with its leverage. Dividing the numerator and denominator of Equation (A29) by $1-F(\bar{x}_j)$ yields:

$$\Lambda(\bar{x}_j) = \frac{1}{1-\mu\bar{x}_j h(\bar{x}_j)}$$

Differentiating Equation (A29) and inserting Equation (A24) yields:

$$\Lambda'(\bar{x}_j) = \frac{\mu\left[\Gamma'(\bar{x}_j)G''(\bar{x}_j) - \Gamma''(\bar{x}_j)G'(\bar{x}_j)\right]}{\left[\Gamma'(\bar{x}_j) - \mu G'(\bar{x}_j)\right]^2} > 0$$

Since the regularity condition of the log normality of the shocks ω_j implies $\bar{x}_j h(\bar{x}_j) \to 0$ as $\bar{x}_j \to 0$, and since $\mu\bar{x}_j h(\bar{x}_j)$ increases strictly to 1 as $\bar{x}_j \to \bar{x}^*$:

$$\lim_{\bar{x}_j\to 0}\Lambda(\bar{x}_j) = 1 \qquad \text{and} \qquad \lim_{\bar{x}_j\to\bar{x}^*}\Lambda(\bar{x}_j) = +\infty$$

Intuitively, firm j's shadow cost equals 1 when default is negligible and rises with the cutoff because each additional unit promised raises expected verification costs, which firm j ultimately bears. In other words, the riskier firm j is as a borrower, the more costly it is for the firm to promise lenders an additional unit of expected return, since a larger share of each additional unit promised is lost to verification in default.

External Finance Premium. Rearrange Equation (A28) to express the expected marginal return to capital, relative to the gross whole interest rate, as a function of the cutoff:

$$\frac{\alpha\theta\Phi_j K_j^{\alpha\theta-1}}{1+\underline{r}} = S(\bar{x}_j) \equiv \frac{\Lambda(\bar{x}_j)}{\left[1-\Gamma(\bar{x}_j)\right] + \Lambda(\bar{x}_j)\left[\Gamma(\bar{x}_j) - \mu G(\bar{x}_j)\right]} \tag{A30}$$

where $S(\bar{x}_j)$ is the external finance premium. Let $\mathcal{D}(\bar{x}_j)$ denote the denominator of $S(\bar{x}_j)$. The derivative of this denominator with respect to the cutoff is:

$$\mathcal{D}'(\bar{x}_j) = -\Gamma'(\bar{x}_j) + \Lambda'(\bar{x}_j)\left[\Gamma(\bar{x}_j) - \mu G(\bar{x}_j)\right] + \Lambda(\bar{x}_j)\left[\Gamma'(\bar{x}_j) - \mu G'(\bar{x}_j)\right]$$

Since Equation (A29) implies $\Lambda(\bar{x}_j)\left[\Gamma'(\bar{x}_j) - \mu G'(\bar{x}_j)\right] = \Gamma'(\bar{x}_j)$:

$$\mathcal{D}'(\bar{x}_j) = \Lambda'(\bar{x}_j)\left[\Gamma(\bar{x}_j) - \mu G(\bar{x}_j)\right]$$

$$\implies S'(\bar{x}_j) = S(\bar{x}_j)\left[\frac{\Lambda'(\bar{x}_j)}{\Lambda(\bar{x}_j)} - \frac{\mathcal{D}'(\bar{x}_j)}{\mathcal{D}(\bar{x}_j)}\right] = S(\bar{x}_j)\frac{\Lambda'(\bar{x}_j)}{\Lambda(\bar{x}_j)}\frac{1-\Gamma(\bar{x}_j)}{\mathcal{D}(\bar{x}_j)} > 0$$

Moreover, from the limits of $\Lambda(\bar{x}_j)$:

$$\lim_{\bar{x}_j \to 0} S(\bar{x}_j) = 1 \qquad \text{and} \qquad \lim_{\bar{x}_j \to \bar{x}^*} S(\bar{x}_j) = \frac{1}{\Gamma(\bar{x}^*) - \mu G(\bar{x}^*)}$$

Intuitively, firm j invests until its expected marginal return to capital equals the gross wholesale interest rate scaled up by the premium $S(\bar{x}_j)$, which reflects the expected verification costs that firm j ultimately bears on its marginal unit of capital. When default is negligible, firm j pays no premium and invests as if it could borrow at the wholesale rate. As its cutoff rises, the premium rises with the shadow cost $\Lambda(\bar{x}_j)$ of promising its lender an additional unit of expected return. In other words, riskier borrowers face a higher financing cost.

Leverage. Equation (A30) implies $\Phi_j K_j^{\alpha\theta} = (1+\underline{r})S(\bar{x}_j)K_j/(\alpha\theta)$. Insert this expression into Equation (A22) and divide both sides by $(1+\underline{r})K_j$ to express firm j's leverage $\ell_j \equiv D_j/K_j = 1 - N_j/K_j$ as a function of its cutoff:

$$\ell_j = \ell(\bar{x}_j) \equiv \frac{\left[\Gamma(\bar{x}_j) - \mu G(\bar{x}_j)\right] S(\bar{x}_j)}{\alpha\theta} \tag{A31}$$

Equation (A23) and $S'(\bar{x}_j) > 0$ imply that both terms in the numerator of Equation (A31) are positive and increasing on $(0, \bar{x}^*)$, so $\ell'(\bar{x}_j) > 0$. Moreover, since $\Gamma(\bar{x}_j) - \mu G(\bar{x}_j) \to 0$ and $S(\bar{x}_j) \to 1$ as $\bar{x}_j \to 0$, and since $\left[\Gamma(\bar{x}_j) - \mu G(\bar{x}_j)\right] S(\bar{x}_j) \to 1$ as $\bar{x}_j \to \bar{x}^*$:

$$\lim_{\bar{x}_j \to 0} \ell(\bar{x}_j) = 0 \qquad \text{and} \qquad \lim_{\bar{x}_j \to \bar{x}^*} \ell(\bar{x}_j) = \frac{1}{\alpha\theta} > 1$$

Thus, there exists a unique $\bar{x}_1 \in (0, \bar{x}^*)$ with $\ell(\bar{x}_1) = 1$, and $\ell(\bar{x}_j)$ maps $(0, \bar{x}_1)$ one-to-one onto $(0, 1)$. Every firm with positive net worth therefore has an interior cutoff, and, unlike in Bernanke et al. (1999), no further assumption on the expected return to capital is needed to rule out credit rationing. Define $s(\ell_j) \equiv S\left(\ell^{-1}(\ell_j)\right)$, so that $s'(\ell_j) = S'(\bar{x}_j)/\ell'(\bar{x}_j) > 0$. Equation (A30) then becomes:

$$\alpha\theta\Phi_j K_j^{\alpha\theta-1} = (1 + \underline{r})\, s(\ell_j) \tag{A32}$$

which equates firm j's expected marginal return to capital with its financing cost $(1 + \underline{r})s(\ell_j)$. Thus, firm j's financing cost is strictly increasing in its leverage, and it depends only on ℓ_j, not on A_j, N_j, or Φ_j.

Part (a): Convexity of Log Financing Cost in Log Leverage. Let $H(\bar{x}_j) \equiv \Gamma(\bar{x}_j) - \mu G(\bar{x}_j)$ denote the lender's expected net share. Equation (A31) implies $S(\bar{x}_j) = \alpha\theta\ell_j / H(\bar{x}_j)$, so firm j's log financing cost is:

$$\ln\left[(1 + \underline{r})s(\ell_j)\right] = \ln\left[(1 + \underline{r})\alpha\theta\right] + \ln \ell_j - \ln H(\bar{x}_j) \tag{A33}$$

Differentiating Equation (A33) with respect to $\ln \ell_j$ yields the elasticity of firm j's financing cost with respect to its leverage:

$$\varepsilon(\ell_j) \equiv \frac{d \ln\left[(1 + \underline{r})s(\ell_j)\right]}{d \ln \ell_j} = 1 - \frac{d \ln H(\bar{x}_j)}{d \ln \ell_j} \tag{A34}$$

Thus, a 1% increase in firm j's leverage is split between a rise in its lender's expected net share and a rise in its external finance premium, and its log financing cost is convex in its log leverage wherever its lender's log expected net share is concave in it.

To characterize $d \ln H(\bar{x}_j)/d \ln \ell_j$, insert $S(\bar{x}_j) = \Lambda(\bar{x}_j)/\mathcal{D}(\bar{x}_j)$ into Equation (A31):

$$\alpha\theta\ell_j = \frac{\Lambda(\bar{x}_j)H(\bar{x}_j)}{\Lambda(\bar{x}_j)H(\bar{x}_j) + \left[1 - \Gamma(\bar{x}_j)\right]}$$

so that $1 - \alpha\theta\ell_j = \left[1 - \Gamma(\bar{x}_j)\right]/\mathcal{D}(\bar{x}_j)$. Take the natural logarithm of this expression and differentiate it with respect to $\bar{x}_j$, using $\Lambda(\bar{x}_j)H'(\bar{x}_j) = \Gamma'(\bar{x}_j)$ from Equation (A29):

$$\frac{\ell'(\bar{x}_j)}{\ell(\bar{x}_j)} = \frac{\Lambda'(\bar{x}_j)H(\bar{x}_j) + \Gamma'(\bar{x}_j)}{\Lambda(\bar{x}_j)H(\bar{x}_j)} - \frac{\Lambda'(\bar{x}_j)H(\bar{x}_j)}{\mathcal{D}(\bar{x}_j)}$$

$$\implies \frac{\ell'(\bar{x}_j)}{\ell(\bar{x}_j)} = \frac{\Gamma'(\bar{x}_j) + \left(1 - \alpha\theta\ell_j\right)\Lambda'(\bar{x}_j)H(\bar{x}_j)}{\Lambda(\bar{x}_j)H(\bar{x}_j)}$$

Dividing $H'(\bar{x}_j)/H(\bar{x}_j) = \Gamma'(\bar{x}_j)/\left[\Lambda(\bar{x}_j)H(\bar{x}_j)\right]$ by this expression and inserting the result into Equation (A34):

$$\varepsilon(\ell_j) = \frac{\Omega(\bar{x}_j)}{1 + \Omega(\bar{x}_j)}, \qquad \Omega(\bar{x}_j) \equiv \left(1 - \alpha\theta\ell_j\right)\frac{\Lambda'(\bar{x}_j)H(\bar{x}_j)}{\Gamma'(\bar{x}_j)} \tag{A35}$$

Since $\ell'(\bar{x}_j) > 0$, Equation (A35) implies that firm j's log financing cost is convex in its log leverage wherever $\Omega(\bar{x}_j)$ is increasing in $\bar{x}_j$. Intuitively, $\Omega(\bar{x}_j)$ measures how strongly the shadow cost of promising additional repayment rises with the cutoff, relative to the lender's expected net share.

Now, it is necessary to use the regularity condition that the distribution of x_j is log-normal. Let $z_j \equiv (\ln \bar{x}_j + \sigma^2/2)/\sigma$, and let $\mathcal{N}(\cdot)$, $\mathcal{N}'(\cdot)$, and $M(\cdot) \equiv \mathcal{N}'(\cdot)/\left[1 - \mathcal{N}(\cdot)\right]$ denote the standard normal cumulative distribution function, probability density function, and inverse Mills ratio, respectively. Log normality then implies $\bar{x}_j = e^{\sigma z_j - \sigma^2/2}$, $\Gamma'(\bar{x}_j) = 1 - \mathcal{N}(z_j)$, $H(\bar{x}_j) = (1-\mu)\mathcal{N}(z_j - \sigma) + \bar{x}_j\left[1 - \mathcal{N}(z_j)\right]$, $\bar{x}_j h(\bar{x}_j) = M(z_j)/\sigma$, and, since $d\left[\bar{x}_j h(\bar{x}_j)\right]/d\bar{x}_j = M(z_j)\left[M(z_j) - z_j\right]/(\sigma^2 \bar{x}_j)$,

$$\Lambda'(\bar{x}_j) = \frac{\mu\, M(z_j)\left[M(z_j) - z_j\right]}{\sigma^2\, \bar{x}_j \left[1 - \mu M(z_j)/\sigma\right]^2}$$

Inserting these expressions into Equation (A35):

$$\Omega(\bar{x}_j) = \left(1 - \alpha\theta\ell_j\right)\frac{\mu\, M(z_j)\left[M(z_j) - z_j\right] H(\bar{x}_j)}{\sigma^2\, \bar{x}_j \left[1 - \mathcal{N}(z_j)\right]\left[1 - \mu M(z_j)/\sigma\right]^2} \tag{A36}$$

where $\alpha\theta\ell_j = \Lambda(\bar{x}_j)H(\bar{x}_j)/\mathcal{D}(\bar{x}_j)$ depends only on z_j, μ, and σ. Thus, Ω is a function of z_j alone, given μ and σ.

To characterize where Ω is increasing, consider first its behavior at low leverage, i.e., as $z_j \to -\infty$. In this limit, $\bar{x}_j \to 0$, $\mathcal{N}(z_j) \to 0$, $M(z_j) \to 0$, $M(z_j)\left[M(z_j) - z_j\right] \to 0$, $H(\bar{x}_j)/\bar{x}_j \to 1$, and $\alpha\theta\ell_j \to 0$. Equation (A36) therefore implies:

$$\lim_{z_j \to -\infty} \Omega(\bar{x}_j) = 0$$

Next, take the natural logarithm of Equation (A36) and differentiate it with respect to z_j, using $d\bar{x}_j/dz_j = \sigma\bar{x}_j$, $M'(z_j) = M(z_j)\left[M(z_j) - z_j\right]$, and:

$$\begin{aligned} dH(\bar{x}_j)/dz_j &= \sigma\bar{x}_j\left[1-\mathcal{N}(z_j)\right]\left[1-\mu M(z_j)/\sigma\right] \\ \implies \frac{d\ln\Omega(\bar{x}_j)}{dz_j} &= \underbrace{M(z_j)-z_j}_{\to+\infty} + \underbrace{\frac{M'(z_j)-1}{M(z_j)-z_j}}_{\to 0} + \underbrace{M(z_j)}_{\to 0} \\ &\quad + \underbrace{\sigma\left[\frac{\bar{x}_j\left[1-\mathcal{N}(z_j)\right]\left[1-\mu M(z_j)/\sigma\right]}{H(\bar{x}_j)} - 1\right]}_{\to 0} \\ &\quad + \underbrace{\frac{2\mu M'(z_j)/\sigma}{1-\mu M(z_j)/\sigma}}_{\to 0} \\ &\quad + \underbrace{\frac{d\ln\left(1-\alpha\theta\ell_j\right)}{dz_j}}_{\to 0} \end{aligned} \tag{A37}$$

The first term on the right-hand side is the derivative of $\ln M(z_j)$, the second that of $\ln\left[M(z_j) - z_j\right]$, the third that of $-\ln\left[1-\mathcal{N}(z_j)\right]$, the fourth that of $\ln H(\bar{x}_j) - \ln\bar{x}_j$, the fifth that of $-2\ln\left[1-\mu M(z_j)/\sigma\right]$, and the last that of $\ln\left(1-\alpha\theta\ell_j\right)$, which converges to 0 because $\alpha\theta\ell_j \to 0$ and $d\ln\ell_j/dz_j \to \sigma$.[38] Since the first term diverges while all others converge to 0, $d\ln\Omega(\bar{x}_j)/dz_j \to +\infty$ as $z_j \to -\infty$. Hence, there exists $\underline{z}$ such that Ω is strictly increasing in z_j for all $z_j < \underline{z}$.

Taken together, Ω starts from 0 at arbitrarily low leverage and initially increases with the cutoff. Whether and where it eventually stops increasing depends on the parameters. Let $z_c(\mu,\sigma)$ denote the supremum of z such that Ω is strictly increasing on $(-\infty, z)$, which the previous step shows to satisfy $z_c(\mu,\sigma) > -\infty$, and let $\kappa(\mu,\sigma) \in (0,1]$ denote scaled leverage $\alpha\theta\ell_j$ evaluated at $z_c(\mu,\sigma)$. Since $\ell_j = \alpha\theta\ell_j/(\alpha\theta)$ and $\alpha\theta\ell_j$ is strictly increasing in z_j, firm j's log financing cost $\ln\left[(1+\underline{r})s(\ell_j)\right]$ is strictly convex in its log leverage $\ln\ell_j$ for all $\ell_j \in (0,\bar{\ell})$, where:

$$\bar{\ell} \equiv \min\left\{1,\ \frac{\kappa(\mu,\sigma)}{\alpha\theta}\right\} > 0 \tag{A38}$$

[38] Multiplying the expression for $\ell'(\bar{x}_j)/\ell(\bar{x}_j)$ above Equation (A35) by $d\bar{x}_j/dz_j = \sigma\bar{x}_j$ yields $d\ln\ell_j/dz_j = \sigma\bar{x}_j\Gamma'(\bar{x}_j)/\left[\Lambda(\bar{x}_j)H(\bar{x}_j)\right] + \sigma\left(1-\alpha\theta\ell_j\right)\bar{x}_j\Lambda'(\bar{x}_j)/\Lambda(\bar{x}_j)$. As $z_j \to -\infty$, the first term converges to σ because $\bar{x}_j/H(\bar{x}_j) \to 1$, $\Gamma'(\bar{x}_j) \to 1$, and $\Lambda(\bar{x}_j) \to 1$, while the second converges to 0 because $\bar{x}_j\Lambda'(\bar{x}_j)$ is proportional to $M(z_j)\left[M(z_j) - z_j\right] \to 0$.

This proves part (a) of Proposition 2. Intuitively, when firm j's leverage is low, its probability of default is negligible, so its lender's expected net share rises almost one-for-one with its leverage, and its financing cost is nearly flat. As its leverage rises, a growing share of each additional unit promised is lost to verification in default, so its lender's expected net share rises less than proportionally, and its external finance premium absorbs an increasing share of each additional unit of leverage.

Part (b): Steepness of the Financing-Cost Curve. In Section 2.1, λ_j is the elasticity of firm j's financing-cost curve $\rho_j(K_j)$ with respect to its capital, which also equals the elasticity of its marginal cost of capital $(1+\lambda_j)\rho_j(K_j)$ in Equation (A1). Equation (A32) shows that firm j's marginal cost of capital in the extended model is $(1+\underline{r})s(\ell_j)$, where $\ell_j = 1 - N_j/K_j$. Holding its net worth N_j fixed, define λ_j as the local elasticity of this marginal cost with respect to K_j. Since $d\ell_j/d\ln K_j = N_j/K_j = 1-\ell_j$:

$$\lambda_j \equiv \left.\frac{d\ln\left[(1+\underline{r})s(\ell_j)\right]}{d\ln K_j}\right|_{N_j} = \varepsilon(\ell_j)\,\frac{d\ln\ell_j}{d\ln K_j} = \varepsilon(\ell_j)\,\frac{1-\ell_j}{\ell_j} \tag{A39}$$

Like $\varepsilon(\ell_j)$, λ_j depends only on firm j's leverage, and it is strictly positive for $\ell_j \in (0,1)$. Insert Equation (A35) into Equation (A39), take the natural logarithm, and differentiate it with respect to z_j, using $d\ln(1-\ell_j)/dz_j = -\left[\ell_j/(1-\ell_j)\right] d\ln\ell_j/dz_j$:

$$\ln\lambda_j = \ln\Omega(\bar{x}_j) - \ln\left[1+\Omega(\bar{x}_j)\right] + \ln(1-\ell_j) - \ln\ell_j$$

$$\implies \frac{d\ln\lambda_j}{dz_j} = \frac{1}{1+\Omega(\bar{x}_j)}\,\frac{d\ln\Omega(\bar{x}_j)}{dz_j} - \frac{1}{1-\ell_j}\,\frac{d\ln\ell_j}{dz_j} \tag{A40}$$

The first term in Equation (A40) reflects the increasing elasticity of firm j's financing cost with respect to its leverage characterized in part (a). The second term, which is strictly negative since $d\ln\ell_j/dz_j > 0$, reflects that a given percentage increase in firm j's capital raises its leverage by less, the higher its leverage already is. Thus, λ_j is strictly increasing in ℓ_j only where Ω is not only increasing but increasing sufficiently fast.

As $z_j \to -\infty$, Equation (A37) and $\Omega(\bar{x}_j) \to 0$ imply that the first term in Equation (A40) diverges to $+\infty$, while $\ell_j \to 0$ and $d\ln\ell_j/dz_j \to \sigma$ imply that the second term converges to $-\sigma$. Hence, $d\ln\lambda_j/dz_j \to +\infty$, so there exists $\underline{z}'$ such that λ_j is strictly increasing in z_j, and therefore in ℓ_j, for all $z_j < \underline{z}'$. However, λ_j cannot be increasing at all levels of leverage: as $\ell_j \to 1$, $\varepsilon(\ell_j) = \Omega(\bar{x}_j)/\left[1+\Omega(\bar{x}_j)\right] < 1$ and $1-\ell_j \to 0$, so Equation (A39) implies $\lambda_j \to 0$. Thus, λ_j rises at low leverage before eventually falling back toward 0 as leverage approaches 1. Define the threshold:

$$\hat{\ell} \equiv \sup\left\{\ell' \in (0,1] : \ \lambda_j \text{ is strictly increasing in } \ell_j \text{ on } (0,\ell')\right\} \tag{A41}$$

The previous two steps imply $0 < \hat{\ell} < 1$, and Equation (A40) implies $\hat{\ell} \leq \bar{\ell}$, since $d \ln \lambda_j / dz_j < 0$ wherever Ω is not increasing. Hence, for $\ell_j = D_{j0}/K_{j0} < \hat{\ell}$, firms with higher initial leverage are at steeper points in their financing-cost curves, proving part (b) of Proposition 2. Unlike $\bar{\ell}$, $\hat{\ell}$ depends on $\alpha\theta$ not only through the domain of leverage but also through the term $(1-\ell_j)/\ell_j$ in Equation (A39).

Intuitively, at low leverage, additional borrowing barely raises firm j's probability of default, so its financing cost is nearly flat in its capital. As leverage rises, the financing cost becomes increasingly sensitive to leverage, as shown in part (a), so its financing-cost curve steepens. At sufficiently high leverage, however, further increases in capital raise leverage only slightly, since firm j's debt already funds nearly all of its capital, so the financing-cost curve flattens again.

How high this threshold lies is a quantitative question. Calibrating the verification cost to $\mu = 0.12$ and the standard deviation of $\ln x_j$ to $\sigma = 0.28$, consistent with the calibration of Bernanke et al. (1999), yields $\hat{\ell} \approx 0.79$ for a labor supply elasticity of $\beta = 4$ and $\hat{\ell} \in [0.65, 0.85]$ for values of $\alpha\theta$ ranging from 0.56 to 1, the latter corresponding to the constant returns to capital in Bernanke et al. (1999).[39] For comparison, the 75th and 90th percentiles of the 2010 leverage distribution across the firms in my sample described in Section 5.1 are 0.52 and 0.80, respectively. Thus, under this calibration, λ_j is increasing in leverage for the large majority of these firms, and only the most highly leveraged firms lie in the range in which their financing-cost curves flatten again.

Sources of Heterogeneity in Initial Leverage. Parts (a) and (b) compare firms by their leverage ℓ_j, which is itself an equilibrium outcome. In the model, firms differ only in their total factor productivity A_j and net worth N_j, so any differences in their initial leverage must arise from differences in these exogenous parameters (see Section 2.2). To characterize how, insert $K_j = N_j/(1-\ell_j)$ into Equation (A32) and rearrange terms:

$$\alpha\theta\, \Phi_j N_j^{-(1-\alpha\theta)} \left(1-\ell_j\right)^{1-\alpha\theta} = (1+\underline{r})\, s(\ell_j) \tag{A42}$$

Since $\alpha\theta < 1$, the left-hand side of Equation (A42) is strictly decreasing in ℓ_j, while the right-hand side is strictly increasing in ℓ_j. Equation (A42) therefore has a unique solution with $\ell_j \in (0,1)$ whenever its left-hand side exceeds $1+\underline{r}$ at $\ell_j = 0$, i.e., whenever firm j borrows, and this solution is strictly increasing in the index $\Phi_j N_j^{-(1-\alpha\theta)}$.

[39] These values fix $\alpha = 0.3$. Numerically, $\hat{\ell}$ does not vary with μ, which scales the level of λ_j but not the location of its peak. Since ω in Bernanke et al. (1999) multiplies a firm's entire return to capital, it corresponds to x_j rather than ω_j in my model.

This index measures firm j's expected return to capital relative to its internal funds: a higher Φ_j raises firm j's demand for capital, while a higher N_j reduces the borrowing required to finance any given capital stock.

The definition of Φ_j following Equation (A18) implies that, for two firms i and j in the same labor market, which therefore face the same W, $\Phi_i/\Phi_j = (A_i/A_j)^\theta$. Hence, firm i has higher leverage than firm j if and only if:

$$\theta \ln\left(\frac{A_i}{A_j}\right) > (1-\alpha\theta)\ln\left(\frac{N_i}{N_j}\right) \iff \ln\left(\frac{A_i}{A_j}\right) > \frac{1-\alpha}{1+\beta}\ln\left(\frac{N_i}{N_j}\right) \tag{A43}$$

where the equivalence uses $(1-\alpha\theta)/\theta = (1-\alpha)/(1+\beta)$. Productivity enters the index with the weight $\theta > 1$ because, as shown in Equation (A18), firm j's optimal ex-post hiring amplifies the effect of A_j on its net-of-wages profits. Net worth instead enters with the weight $1-\alpha\theta < 1$, since decreasing returns to capital arising from firms' monopsony power over workers limit how much a firm's demand for capital scales with its internal funds. Firm leverage therefore indicates that a firm's productivity is high relative to its net worth in the sense of Equation (A43). This interpretation is consistent with Table 4, which shows that younger firms, which have had less time to accumulate net worth, tend to have higher leverage.

Importantly, λ_j depends only on ℓ_j, and the firm-level responses to immigration characterized in Proposition 1 depend on firm j's characteristics only through λ_j. Thus, in the model, any combination of differences in A_j and N_j that generates the same difference in initial leverage below $\hat{\ell}$ generates the same difference in λ_j, and therefore the same differences in the responses predicted by parts (c) and (d). Beyond the model, differences in productivity or net worth could also shape firms' responses to immigration through other channels, for instance if more productive firms face different labor supply elasticities. The cell fixed effects for firms' sector, cohort, size, and skill intensity described in Section 4.3 absorb such differences insofar as they are common to firms with similar initial characteristics.

Parts (c) and (d): Effects of Immigration by Initial Leverage. I now show that, with λ_j defined by Equation (A39) and evaluated at firm j's initial leverage, firm j's responses to the market-level immigration shock dI are identical to those characterized in Appendix A.1, so that parts (c) and (d) of Proposition 2 follow from Proposition 1 and part (b). Since firm j's net worth N_j is predetermined, I hold it fixed. Moreover, Equation (A32) shows that the immigration shock affects firm j's choice of capital only through Φ_j, and hence through W, but not through its financing cost $(1+\underline{r})s(\ell_j)$, which depends only on its leverage.

First, take the natural logarithm of Equation (A32) and totally differentiate it holding N_j fixed, using the definition of λ_j in Equation (A39):

$$d\ln\Phi_j - (1-\alpha\theta)\,d\ln K_j = \lambda_j\,d\ln K_j$$

$$\implies d\ln K_j = \frac{d\ln\Phi_j}{1-\alpha\theta+\lambda_j} \tag{A44}$$

The definitions of Φ_j and W imply

$$d\ln\Phi_j = -(\theta-1)\,d\ln W,$$
$$d\ln W = -\frac{1}{\beta}\,d\ln\left(\frac{\bar{L}}{\sum_{j'\in\mathcal{J}} w_{j'}^{\beta}}\right).$$

Insert these expressions into Equation (A44), using $\theta - 1 = \beta(1-\alpha)/(1+\alpha\beta)$ and $1-\alpha\theta = (1-\alpha)/(1+\alpha\beta)$:

$$\frac{d\ln K_j}{d\ln\left(\frac{\bar{L}}{\sum_{j'\in\mathcal{J}} w_{j'}^{\beta}}\right)} = \frac{1-\alpha}{1-\alpha+\lambda_j(1+\alpha\beta)} \tag{A45}$$

Second, take the natural logarithm of Equation (A17) and totally differentiate it for a given realization of ω_j, and insert Equation (A45):

$$d\ln L_j = \frac{\beta}{1+\alpha\beta}\left[\alpha\,d\ln K_j - d\ln W\right] = \frac{1}{1+\alpha\beta}\left[\alpha\beta\,d\ln K_j + d\ln\left(\frac{\bar{L}}{\sum_{j'\in\mathcal{J}} w_{j'}^{\beta}}\right)\right]$$

$$\implies \frac{d\ln L_j}{d\ln\left(\frac{\bar{L}}{\sum_{j'\in\mathcal{J}} w_{j'}^{\beta}}\right)} = \frac{1-\alpha+\lambda_j}{1-\alpha+\lambda_j(1+\alpha\beta)} \tag{A46}$$

which is identical to Equation (A6). Subtracting Equation (A46) from Equation (A45) yields Equation (A7) for capital intensity. Likewise, since $w(L_j) = WL_j^{1/\beta}$ implies $d\ln w_j = d\ln W + d\ln L_j/\beta$, inserting Equation (A46) yields Equation (A8) for wages. Importantly, ω_j cancels out of these log changes, so they hold for every realization of firm j's productivity shock.

Third, since each firm's wage elasticity with respect to $\bar{L}/\sum_{j'\in\mathcal{J}} w_{j'}^{\beta}$ is again given by Equation (A8), the derivation of Equation (A9) applies unchanged, with the employ-

ment shares $L_{j'}/L$ now averaging over both firms and their realizations of $\omega_{j'}$. The resulting term C remains common to all firms and still satisfies $C > 1/(1+\alpha\beta) > 0$, since this bound relies only on $\lambda_{j'} \geq 0$. Equations (A10)–(A14) therefore hold with λ_j given by Equation (A39). Since Proposition 1 is a first-order characterization around the initial equilibrium, λ_j is evaluated at firm j's initial leverage D_{j0}/K_{j0}; the change in firm j's leverage induced by the immigration shock affects its responses only at second order.

Part (c) of Proposition 2 then follows directly from part (a) of Proposition 1: if $\bar{L}^{imm}/\bar{L} \approx 0$, Equation (A14) implies that each firm's immigrant hiring relative to its initial total employment is approximately dI, regardless of its λ_j and hence of its initial leverage. Finally, part (d) of Proposition 2 follows from combining part (b) of Proposition 1 with part (b) of Proposition 2. Equations (A10), (A11), and (A13) show that the proportional changes in capital intensity and wages and the change in native employment relative to initial total employment are strictly decreasing in λ_j, while part (b) of Proposition 2 shows that λ_j is strictly increasing in initial leverage D_{j0}/K_{j0} below $\hat{\ell}$. Hence, among firms with initial leverage below $\hat{\ell}$, initially higher-leverage firms experience more negative changes in their capital intensity, wages, and native employment in response to immigration, completing the proof of Proposition 2.

Appendix B: Data

This appendix describes the four data sources that I combine in the paper and how I prepare each of them. Section B.1 describes the worker-level social security records from the Sample of Integrated Labour Market Biographies, based on which I characterize immigration to Germany and construct labor market outcomes at the commuting zone level. Section B.2 describes the firm-level financial statements from Moody's DataHub. Section B.3 describes the national accounts data from which I construct the price deflator for tangible fixed assets. Section B.4 describes the establishment-level social security records from the Establishment History Panel and how I link them to the enterprise-level financial statements from Moody's DataHub.

B.1 Sample of Integrated Labour Market Biographies

I use version 7523 v2 of the Sample of Integrated Labour Market Biographies (SIAB), a 2% random sample of the individuals in the Integrated Employment Biographies of the Institute for Employment Research (Graf et al., 2025; Schmucker and Berge, 2025). For each of the individuals in the sample, I observe every spell during which they were an employee (other than a civil servant or a member of the military), a jobseeker, a social security benefit recipient, or a participant in employment and training measures.

Natives and Immigrants. The data reports each individual's nationality as of each spell, distinguishing between 224 nationalities: 195 states of the United Nations, 3 states with limited recognition, 14 dependent territories, 8 states that have ceased to exist (e.g., Yugoslavia), and 4 categories of missing nationality. I first reassign each spell recorded with a state that has ceased to exist to one of its successor states: to the successor state most frequently recorded for that individual if they were ever recorded with one, and otherwise to the successor state most frequently recorded for all individuals. I then combine 2 of the categories of missing nationality ("Unknown" and "No entry") into a single category, but keep "Foreign countries, unknown" and "Stateless" separate, since they contain information about an individual's foreign nationality. I next define an immigrant as an individual ever recorded with one of the 213 remaining foreign nationalities, assign each immigrant the foreign nationality most frequently recorded for them, and classify the negligible share of individuals whose nationality is always missing as immigrants of unknown origin. Finally, for the purposes of constructing the ethnic-enclave shift-share instruments defined in Section 4.2, I keep as distinct only the 74 origin countries which satisfy the IAB's statistical disclosure requirements that there be at least 20 worker-level observations in 1993, 2010, and 2019. I therefore group the remaining 140 into a single "Other" category.

Employment States. I distinguish between five types of spells: unemployment, other non-employment, marginal employment, part-time employment, and full-time employment. I classify as unemployment all jobseeker spells of individuals who were unemployed and willing and able to work (Kruppe et al., 2008). I classify as other non-employment all remaining non-employment spells (e.g., benefit recipient spells) and employment spells not originally classified as either marginal or regular employment (e.g., trainee spells). I classify as marginal employment all remaining employment spells originally classified as such or with a wage at or below the marginal wage threshold (Stüber et al., 2023). I classify as part-time employment all remaining employment spells originally classified as such or assigned a sufficiently low full-time weight by the correction procedure of Fitzenberger and Seidlitz (2020), which smooths over the 2011 break in the part-time indicator (Schmucker and Berge, 2025). In each year, I choose the threshold for the full-time weight so that the number of employees classified as full-time equals the sum of the weights. I classify all remaining employment spells as full-time employment.

Daily Wages. The SIAB does not contain information on hours worked, so I consider the wages of only full-time employees. Since daily wages are right-censored at the social security contribution limit (Schmucker and Berge, 2025), I use the imputed daily wage provided in version 7523 v2 of the SIAB (Graf et al., 2025). This imputation, developed by Drechsler et al. (2023) and Drechsler and Ludsteck (2025), is implemented on the full population of the Integrated Employment Biographies rather than on the 2% sample. It considers three imputation strategies (a right-censored Tobit regression, a doubly censored Tobit regression, and a censored quantile regression) and selects the one that minimizes a sum-of-absolute-deviations criterion for the smoothness of the kernel density estimate of the resulting distribution of daily wages. I deflate the imputed daily wage by Germany's consumer price index as obtained from the German Federal Statistical Office's GENESIS-Online database (see Appendix Section B.3).

Other Characteristics. I define each individual's age as the years since their birth year. I impute their highest educational qualification based on the procedure of Thomsen et al. (2018), which ensures that qualifications weakly increase over time by first forward and then backward extrapolation, and aggregate the 7 qualifications into 3 categories: no vocational training or university degree, vocational training, and university degree. I define each individual's industry and place of work as those of their establishment in the Establishment History Panel (see Appendix Section B.4). I observe each individual's gender. I assign each establishment to one of 12 sectors (see Appendix Table C2) based on its 3-digit industry in the 2008 classification of economic activities (Eberle et al., 2011), and to one of 141 local labor markets (Kosfeld and Werner, 2012) based on its NUTS 3 district. To satisfy statistical disclosure control requirements, I further aggregate adjacent local labor markets into 117 final commuting zones.

Individual-Year Panel. If I observe multiple spells for an individual on a given date, I keep their highest-wage spell of the highest-priority type, with the decreasing order of priority as follows: full-time employment, part-time employment, marginal employment, unemployment, and other non-employment. I restrict the sample to full-time, part-time, and marginal employment spells as of June 30 of each year from 1993 to 2019 for individuals aged 15 to 64. June 30 is the reference date of the Establishment History Panel (Ganzer et al., 2025b), 1993 is the first year for which the data for East Germany is complete (Schmucker and Berge, 2025), and 2019 is the last year before COVID-19.

Commuting Zone-Year Panel. I aggregate the individual-year panel to the commuting zone-year level. I measure employment both in numbers and in full-time equivalent units, separately for all employees, natives, and immigrants. For the full-time equivalent units, I assign a weight of 1 to full-time employment, 0.5 to part-time employment, and 0.2 to marginal employment. I measure commuting zone-level wages as the mean log wage of full-time employees of each type.

B.2 Moody's DataHub

I obtain data on German corporations' financial statements from Moody's DataHub (MDH), the platform through which Moody's (formerly Bureau van Dijk) distributes the data underlying Orbis and Dafne. On March 3, 2026, after restricting the universe of firms to those located in Germany, I downloaded four tables: the *Contact_info*, *Legal_info*, and *Industry_classifications* tables of the *Firmographics (Semi-Annual)* product, and the *industry_global_financials_and_ratios_eur* table of the *Financials History (Semi-Annual)* product. Each firm is identified by its BvD ID number.

Firmographics. The *Contact_info* table contains BvD ID numbers that define the universe of German firms that I consider. From the *Industry_classifications* table, I take each firm's main NACE Rev. 2 section. From the *Legal_info* table, I take each firm's date of incorporation, from which I define its year of incorporation.

Financials History. The *industry_global_financials_and_ratios_eur* table contains firms' financial statements, each identified by a combination of BvD ID number, closing date, consolidation code, and filing type. The consolidation code distinguishes between consolidated statements of firms without (C1) and with (C2) an unconsolidated statement, unconsolidated statements of firms without (U1) and with (U2) a consolidated statement, and limited financials (LF). The filing type distinguishes between statements taken from local registry filings and annual reports. For each statement, I keep the balance sheet items (total, tangible, intangible, and other fixed assets; cash and cash equivalents; total assets; shareholders' funds; long-term debt; and total shareholders' funds and liabilities), number of employees, and interest paid.

Linkable Enterprises. I can only link an enterprise in the data from Moody's DataHub to establishments in the Establishment History Panel (see Appendix Section B.4) if its BvD ID number consists of the ISO country code "DE" followed by the 10-digit Creditreform number. I therefore drop all enterprises that do not satisfy this condition.

Statement Selection. I define each statement's closing month based on its closing date, assign the statement to the calendar year of its closing month, and keep statements closing from 2006 to 2019. I keep only statements with positive tangible fixed assets, which leads limited financials to be dropped. If a firm has multiple statements with the same consolidation code and filing type in a year, I keep the latest. If a firm reports under more than one combination of consolidation code and filing type, I keep a single combination for that firm, in general prioritizing unconsolidated over consolidated statements and local registry filings over annual reports.

Sample Restrictions. Prior to making any of the sample restrictions necessary to each of the analyses as discussed in the main text, I make five general restrictions. First, I drop enterprises with only consolidated statements, because consolidated statements also include the balance sheets of subsidiaries. Second, I drop enterprises ever reporting negative total assets. Third, I drop enterprises ever reporting negative long-term debt. In both cases, such negative values likely reflect reporting errors. Fourth, I drop enterprises with an outlier spinoff, which I define as a large year-on-year decline in tangible fixed assets of at least €1 billion that is offset by an increase in other fixed assets of the same magnitude. Such a change reflects a reclassification of assets rather than disinvestment. Fifth, I drop enterprises with an outlier change in tangible fixed assets, which I define as a year-on-year change exceeding €1 billion in absolute value that amounts to approximately 100% of the stock in the previous or current year. Such a change also likely reflects a reporting error.

B.3 National Accounts

I obtain data on Germany's aggregate stock of fixed assets and consumer price index from the Federal Statistical Office's GENESIS-Online database. Table 81000-0200 reports aggregate stocks since 1991 for 5 economic sectors (the total economy, non-financial corporations, financial corporations, government, and households and non-profit institutions serving households) and different types of fixed assets, including tangible fixed assets. Each stock is reported both gross and net of depreciation, and both at current replacement cost (in billions of euros) and as a price-adjusted chain index (2020 = 100). I use the current replacement cost and price-adjusted chain index series to construct an index to deflate firms' net tangible fixed assets, and I use the consumer price index data from table 61111-0001 to deflate firms' other nominal variables and workers' wages.

Net Tangible Fixed Assets Deflator. Let $K^{\$}_{s,a,t}$ denote the stock of fixed assets of type a in sector s in year t at current replacement cost and $Q_{s,a,t}$ the corresponding chain index. I define the implicit price deflator relative to 2010 as:

$$P_{s,a,t} = \frac{K^{\$}_{s,a,t} / K^{\$}_{s,a,2010}}{Q_{s,a,t} / Q_{s,a,2010}} \tag{B1}$$

and the real stock in 2010 replacement costs as:

$$K_{s,a,t} = \frac{K^{\$}_{s,a,t}}{P_{s,a,t}} = K^{\$}_{s,a,2010} \frac{Q_{s,a,t}}{Q_{s,a,2010}} \tag{B2}$$

I consider the corporate sector, which consists of non-financial and financial corporations, and the net stock of tangible fixed assets. I aggregate the real stocks across the two sectors, $K_{a,t} = \sum_s K_{s,a,t}$, and define the deflator for tangible fixed assets as the ratio of the aggregate stock at current replacement cost to the aggregate real stock:

$$P_t = \frac{\sum_s K^{\$}_{s,a,t}}{\sum_s K_{s,a,t}} \tag{B3}$$

which equals 1 in 2010 and rises to 1.236 in 2019. I deflate each enterprise's tangible fixed assets by P_t to obtain its tangible fixed assets in 2010 replacement costs.

B.4 Custom Link

To link to the enterprise-level financial statements from Moody's DataHub, I obtain establishment-level data from version 7524 of the Establishment History Panel (BHP), which aggregates the worker-level social security records from the Integrated Employment Biographies of the Institute for Employment Research (IAB) to the establishment level as of June 30 of each year (Ganzer et al., 2025a, 2025b). For each establishment and year, I observe the year in which the establishment first appeared in the data, its 3-digit industry in the 2008 classification of economic activities (Eberle et al., 2011), its district, and its numbers of employees, full-time employees, university-educated employees, university-educated full-time employees, native employees, and native full-time employees. I also observe the mean imputed daily wages (see Appendix Section B.1) of full-time employees, university-educated full-time employees, and native full-time employees, which I deflate by the consumer price index (see Appendix Section B.3).

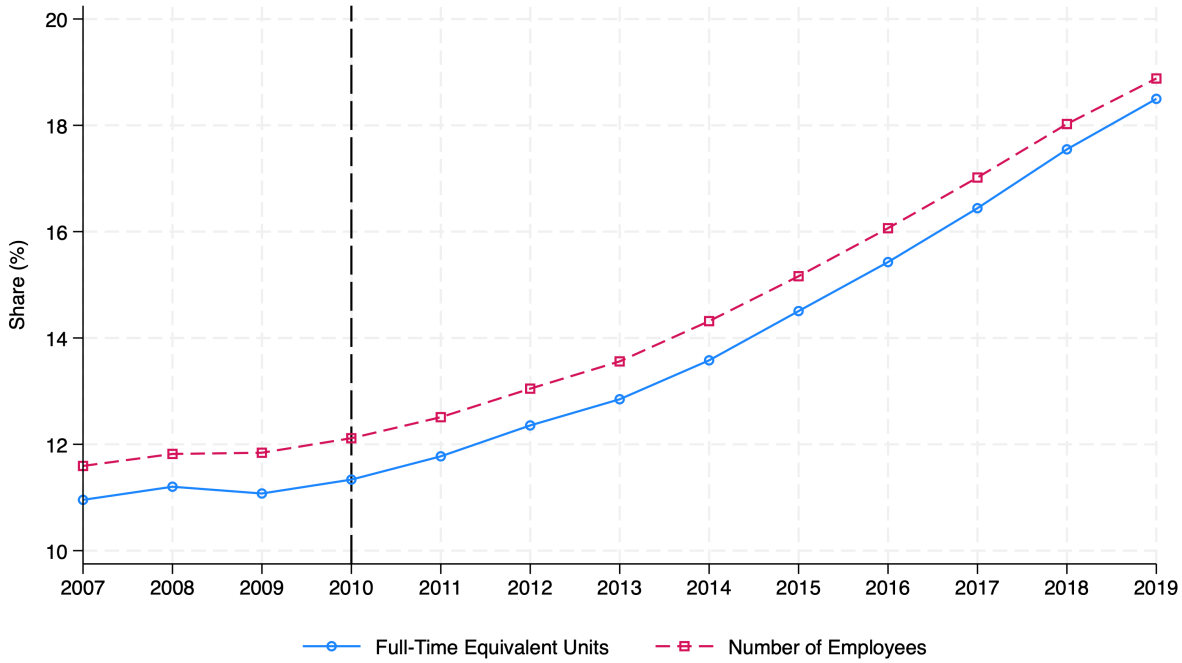
Establishment-Enterprise Link. I exploit a mapping, built by researchers at the IAB and the Zentrum für Europäische Wirtschaftsforschung based on a procedure that matches names and addresses across enterprises and their associated establishments (Doherr, 2023; Diegmann et al., 2024; Gottschalk et al., 2025), between establishment identifiers

from the BHP and enterprise identifiers from Moody's DataHub. Specifically, the IAB provides me with a file that links each establishment to a particular enterprise and the year as of which that link became valid. For each establishment in each year, I keep the enterprise whose link was recorded most recently at or before that year, or, if there is no such link, the enterprise whose link was recorded earliest after that year.

Establishment-Level Financials and Enterprise-Level Payrolls. If an enterprise is linked to multiple establishments in a given year, I distribute each item in its financial statement for that year to each of its establishments in proportion to the number of employees at that establishment. Likewise, I aggregate establishment-level payrolls into enterprise-level payrolls in each year. Specifically, I first sum the numbers of employees of each type across the enterprise's establishments. I then compute the enterprise's mean wage of each type of full-time employee as the average of its establishments' mean wages, weighted by the establishments' numbers of full-time employees of that type.

Appendix C: Descriptives

Figure C1: Immigrant Shares of Employment and Number of Employees



Sources: Sample of Integrated Labour Market Biographies.
Notes: This figure describes the inflows of immigrants into the German labor market from 2007 to 2019, in terms of both full-time equivalent employment and the number of employees. The sample includes workers of ages 15–64 in full-time, part-time, or marginal employment on June 30 of each year. For the purposes of measuring full-time equivalent employment, part-time and marginal workers are assigned weights of 0.5 and 0.2, respectively.

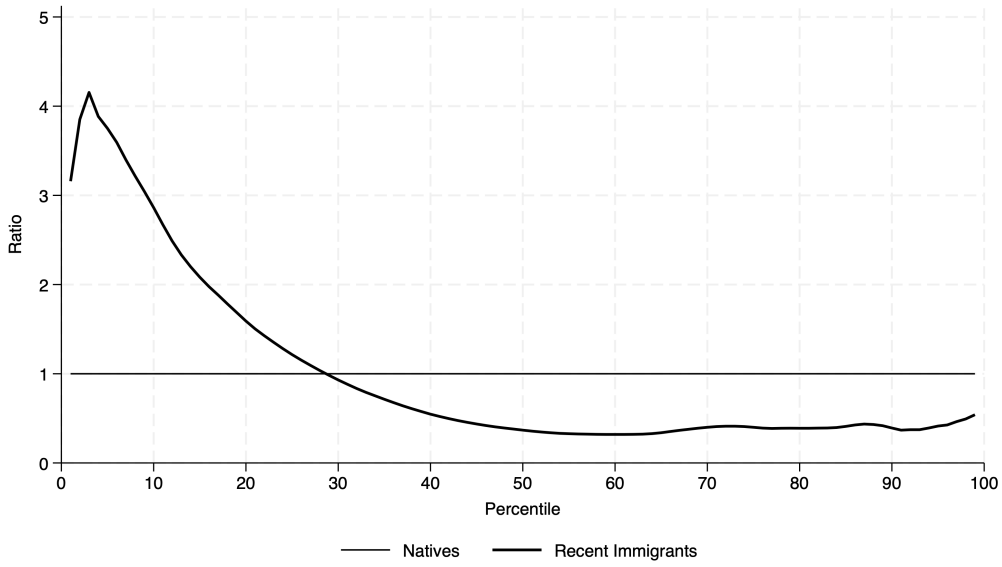
Table C1: Composition of Immigrants by the Reform Affecting Their Origin Country

	Share (%)		
	Earlier		Recent
Reform	1993	2010	2019
Freedom of movement in 2011	7.93	9.66	21.52
Freedom of movement in 2014–2015	13.06	8.08	23.49
Western Balkan Regulation	6.29	8.28	7.43
Suspended Dublin Regulation	1.69	4.02	11.89
Historical migration policies	48.77	48.03	18.08
Other	22.27	21.94	17.58
No. workers	45,091	69,202	53,604

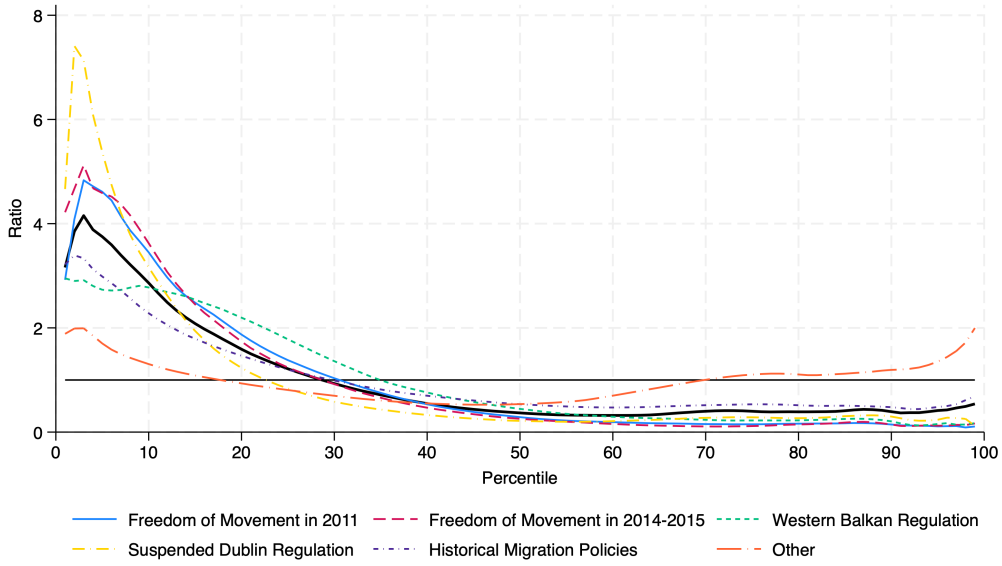
Sources: Sample of Integrated Labour Market Biographies.
Notes: This table summarizes the composition of immigrants by the reform that affected their origin country. Earlier immigrants refer to those who first appear in the data in or before 2010. Recent immigrants refer to those who first appear in the data after 2010. Freedom of movement in 2011 refers to Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, and Slovenia. Freedom of movement in 2014-2015 refers to Bulgaria, Croatia, and Romania. Western Balkan Regulation refers to Albania, Bosnia and Herzegovina, Kosovo, Montenegro, North Macedonia, and Serbia. Suspended Dublin Regulation refers to Afghanistan, Eritrea, Iran, Iraq, Nigeria, Pakistan, Somalia, and Syria. Historical migration policies refers to Greece, Italy, Kazakhstan, Lebanon, Morocco, Portugal, Russia, Spain, Tunisia, Turkey, and Vietnam. Other refers to all other origin countries. The sample includes workers of ages 15–64 in full-time, part-time, or marginal employment on June 30 of each year.

Figure C2: Recent Immigrants' Position in the Native Wage Distribution in 2019

(a) All Recent Immigrants



(b) By the Reform Affecting Their Origin Country



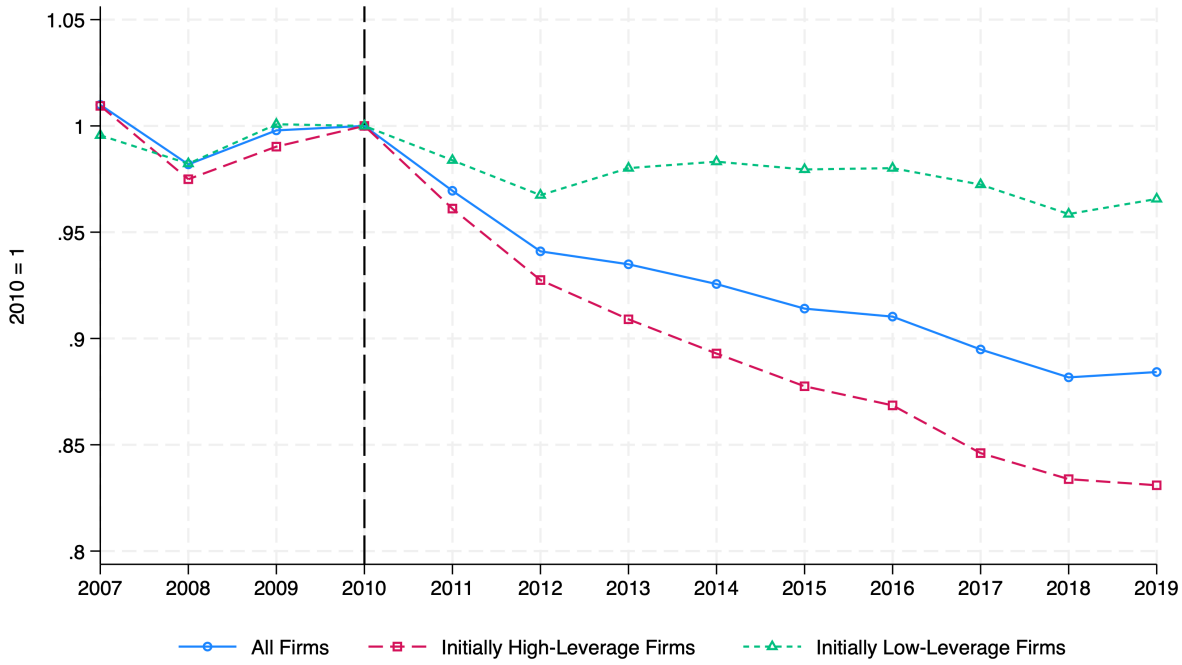
Sources: Sample of Integrated Labour Market Biographies.
Notes: This figure describes the position of recent immigrants in the native wage distribution in 2019, based on transformed kernel density estimates of the log odds of their ranks in that distribution (Dustmann et al., 2013). Recent immigrants refer to those who first appear in the data after 2010. Freedom of Movement in 2011 refers to Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, and Slovenia. Freedom of Movement in 2014-2015 refers to Bulgaria, Croatia, and Romania. Western Balkan Regulation refers to Albania, Bosnia and Herzegovina, Kosovo, Montenegro, North Macedonia, and Serbia. Suspended Dublin Regulation refers to Afghanistan, Eritrea, Iran, Iraq, Nigeria, Pakistan, Somalia, and Syria. Historical Migration Policies refers to Greece, Italy, Kazakhstan, Lebanon, Morocco, Portugal, Russia, Spain, Tunisia, Turkey, and Vietnam. Other refers to all other origin countries. The sample includes workers of ages 15–64 in full-time employment on June 30 of each year.

Table C2: Characteristics of Natives and Immigrants

	Share (%)			
	Natives	Immigrants		
		Earlier		Recent
	2010	1993	2010	2019
Age				
Ages 15–29	18.39	29.43	18.93	36.71
Ages 30–49	52.16	53.62	60.10	53.42
Ages 50–64	29.46	16.95	20.97	9.87
Education				
No vocational training or university	10.09	44.79	35.54	57.93
Apprenticeship-trained	75.19	49.88	53.92	25.30
University-educated	14.71	5.32	10.54	16.77
Gender				
Male	50.45	67.30	54.92	63.86
Female	49.55	32.70	45.08	36.14
Sector				
Manufacturing	20.82	39.84	20.77	12.80
Accommodation and food services	3.46	7.65	10.95	13.63
Construction	5.48	10.79	5.14	9.21
Transportation and storage	5.19	4.59	6.29	9.00
Administrative and support services	5.15	4.32	12.58	16.88
Wholesale and retail trade	15.66	11.05	13.73	10.22
Public administration, education, and health	21.87	9.74	13.01	10.05
Energy, commodities, and utilities	2.61	2.46	2.04	2.36
Real estate and business services	8.39	3.86	6.43	7.52
Information and communication	3.04	0.90	2.25	3.15
Finance and insurance	3.45	1.19	1.22	0.67
Other services	4.89	3.59	5.59	4.49
No. workers	501,993	45,091	69,202	53,604

Sources: Sample of Integrated Labour Market Biographies.
Notes: This table summarizes the characteristics of natives and immigrants by age, education, gender, and sector of employment. Earlier immigrants refer to those who first appear in the data in or before 2010. Recent immigrants refer to those who first appear in the data after 2010. The sample includes workers of ages 15–64 in full-time, part-time, or marginal employment on June 30 of each year.

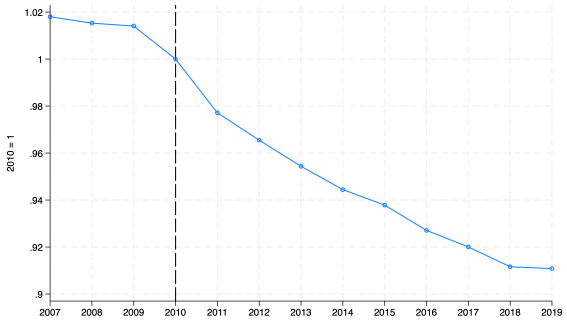
Figure C3: Firms' Capital Intensity Relative to 2010 Including the Largest Firms



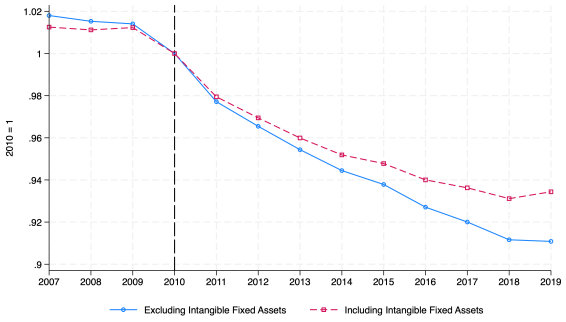
Sources: Moody's DataHub.
Notes: This figure describes the evolution of German firms' net tangible fixed assets per employee from 2007 to 2019, both their aggregate dynamics (i.e., of the total net tangible fixed assets per employee across all firms) and the differences between initially high- and low-leverage firms. Firms are included only if both the numerator and denominator of the ratio are available in all years. Unlike in Figure 2a, the top 1% of firms in terms of maximum size (i.e., number of employees) are included. The last two lines separate firms into two groups based on whether their mean ratio of long-term debt to total assets from 2007 to 2010 was above or below the median.

Figure C4: Firms' Capital Intensity Relative to 2010 according to the National Accounts

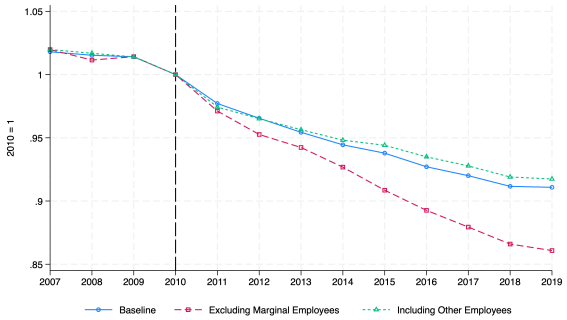
(a) Net Tangible Fixed Assets per Employee



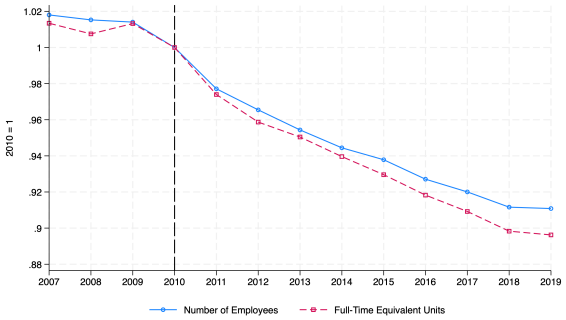
(b) Including vs. Excluding Intangibles



(c) By Type of Employees Included

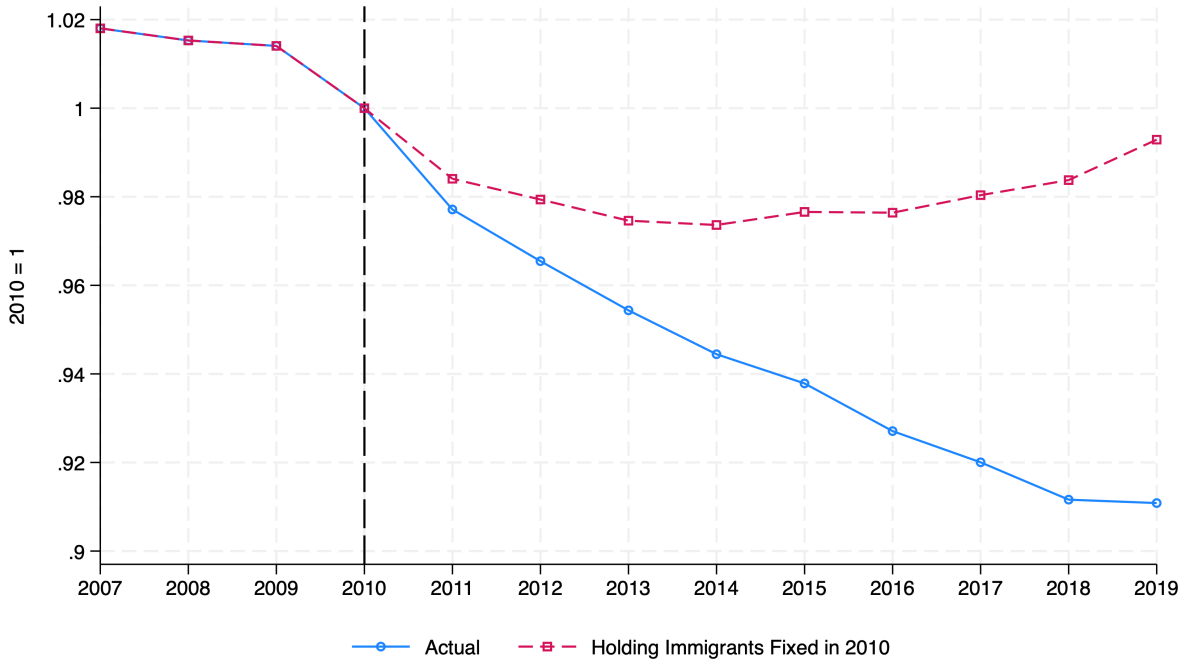


(d) By Full-Time Equivalent Units



Sources: GENESIS-Online; Sample of Integrated Labour Market Biographies.
Notes: This figure describes the evolution of German firms' net tangible fixed assets per employee from 2007 to 2019, based on the total net tangible fixed assets of the corporate sector as a whole according to Germany's national accounts and the total number of employees according to workers' social security records. Panel (a) plots the total net tangible fixed assets per full-time, part-time, or marginal employee relative to 2010 as the baseline. Panel (b) reports the sensitivity of this baseline to including corporations' intangible fixed assets in the numerator. Panel (c) reports the sensitivity of the baseline to excluding marginal workers or including other workers (i.e., those who are employed but not in full-time, part-time, or marginal employment). Panel (d) compares the net tangible fixed assets per employee to the net tangible fixed assets per full-time equivalent unit of employment. For the purposes of constructing the numerator of the ratio, the corporate sector includes both non-financial and financial corporations. For the purposes of constructing the denominator of the ratio, the sample includes workers of ages 15–64 in employment on June 30 of each year.

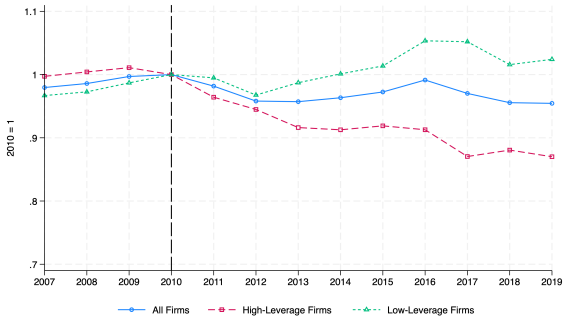
Figure C5: Firms' Capital Intensity Relative to 2010 Holding Immigrants Fixed



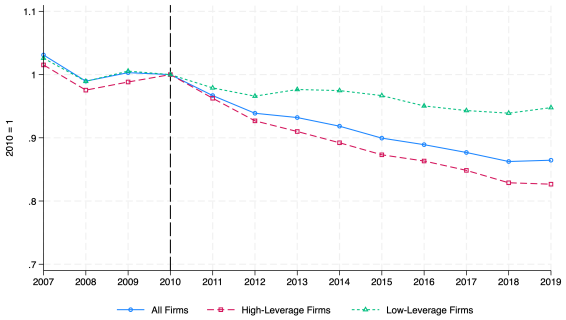
Sources: GENESIS-Online; Sample of Integrated Labour Market Biographies.
Notes: This figure describes the actual evolution of German firms' net tangible fixed assets per employee from 2007 to 2019 and its counterfactual evolution holding immigrants fixed, based on the total net tangible fixed assets of the corporate sector as a whole according to Germany's national accounts and the total number of employees according to workers' social security records. The first line plots the total net tangible fixed assets per full-time, part-time, or marginal employee relative to 2010 as the baseline. The second line plots the same measure but holding the number of immigrant employees fixed at its 2010 level. For the purposes of constructing the numerator of the ratio, the corporate sector includes both non-financial and financial corporations. For the purposes of constructing the denominator of the ratio, the sample includes workers of ages 15–64 in employment on June 30 of each year.

Figure C6: Firms' Capital Intensity Relative to 2010—Heterogeneity

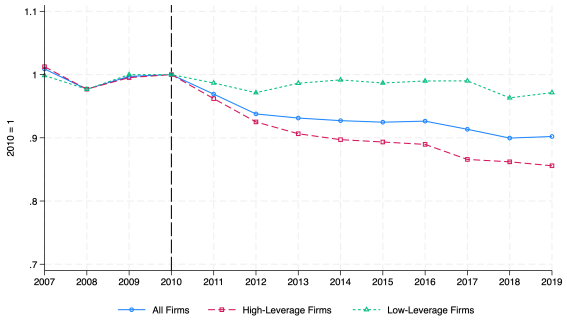
(a) Manufacturing Firms



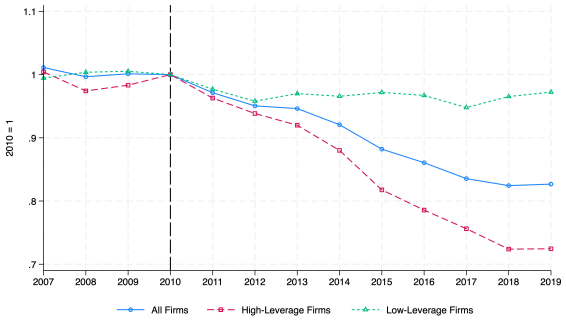
(b) Non-Manufacturing Firms



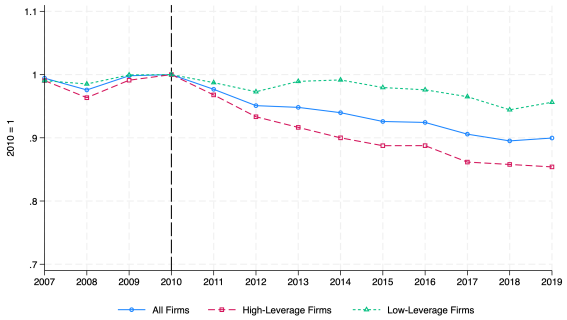
(c) Firms Founded in or before 1995



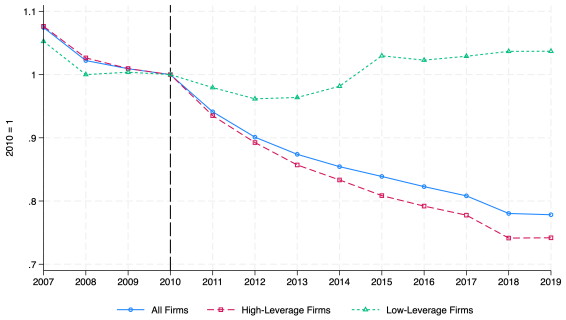
(d) Firms Founded after 1995



(e) Initially Large Firms

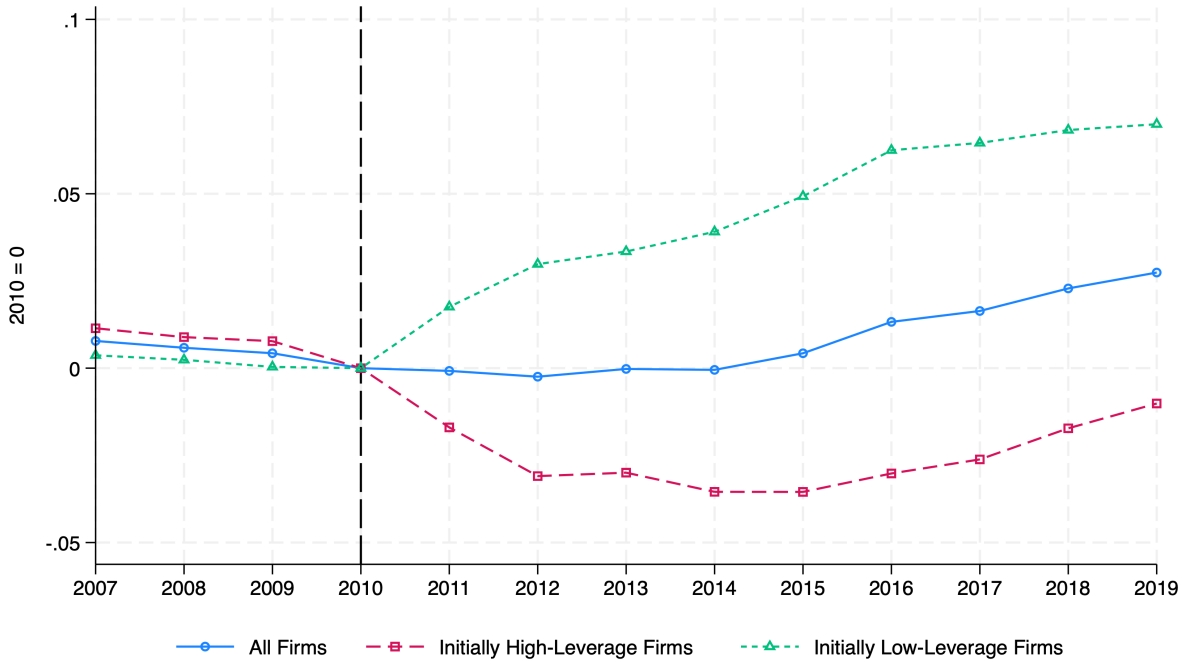


(f) Initially Small Firms



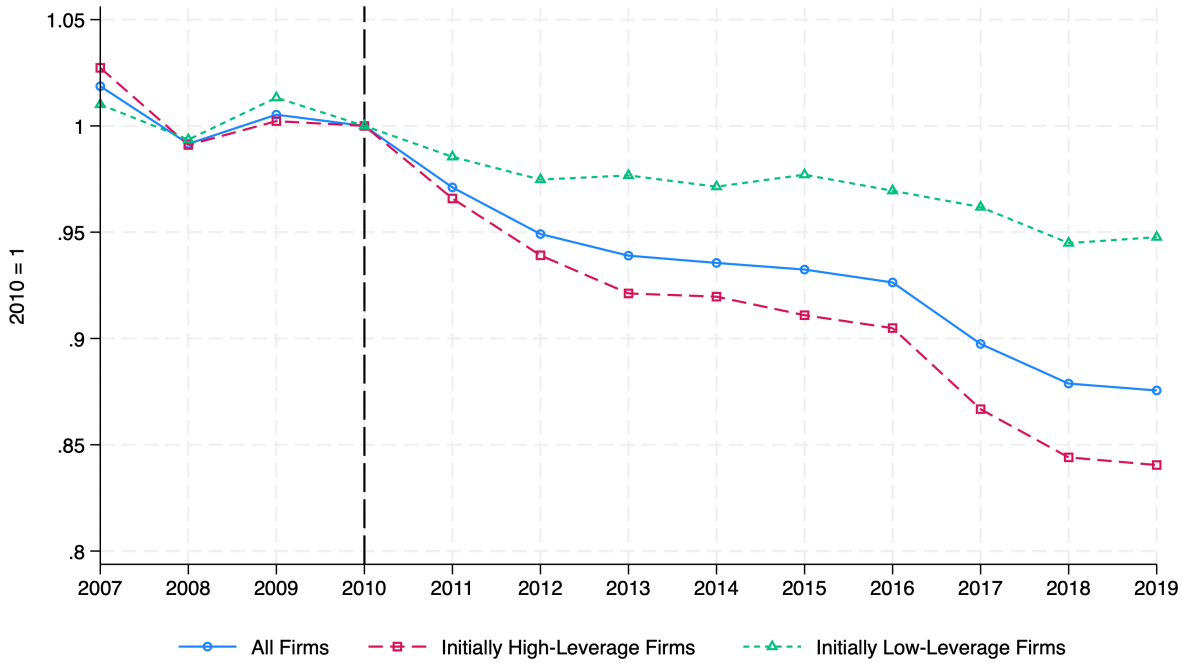
Sources: Moody's DataHub.
Notes: This figure describes the evolution of German firms' capital intensity from 2007 to 2019 for different types of firms, both the aggregate dynamics of each type (i.e., of the total net tangible fixed assets per employee across all the firms of that type) and the differences between initially high- and low-leverage firms of that type. Panel (a) plots manufacturing firms' net tangible fixed assets per employee relative to 2010. Panel (b) plots the same measure for non-manufacturing firms. Panel (c) considers firms founded in or before 1995. Panel (d) considers firms founded after 1995. Panel (e) considers firms in the upper half of the distribution of initial firm size (in terms of the mean log number of employees from 2007 to 2010). Panel (f) considers firms in the lower half of this distribution. Firms are included only if both the numerator and denominator of the ratio are available in all years. Before dividing firms into different types, the top 1% of firms in terms of maximum size are excluded. The last two lines in each panel separate the firms considered within the panel into two groups based on whether their mean ratio of long-term debt to total assets from 2007 to 2010 was above or below the median among those firms.

Figure C7: Firms' Change in Debt Relative to 2010



Sources: Moody's DataHub.
Notes: This figure describes German firms' changes in debt since 2010 relative to their total assets in 2010, both their aggregate dynamics from 2007 to 2019 (i.e., the change in the total long-term debt per euro of 2010 total assets across all firms) and the differences between initially high- and low-leverage firms. Firms are included only if both the numerator and denominator of the ratio are available in all years. The top 1% of firms in terms of maximum size (i.e., number of employees) are excluded. The last two lines separate firms into two groups based on whether their mean ratio of long-term debt to total assets from 2007 to 2010 was above or below the median.

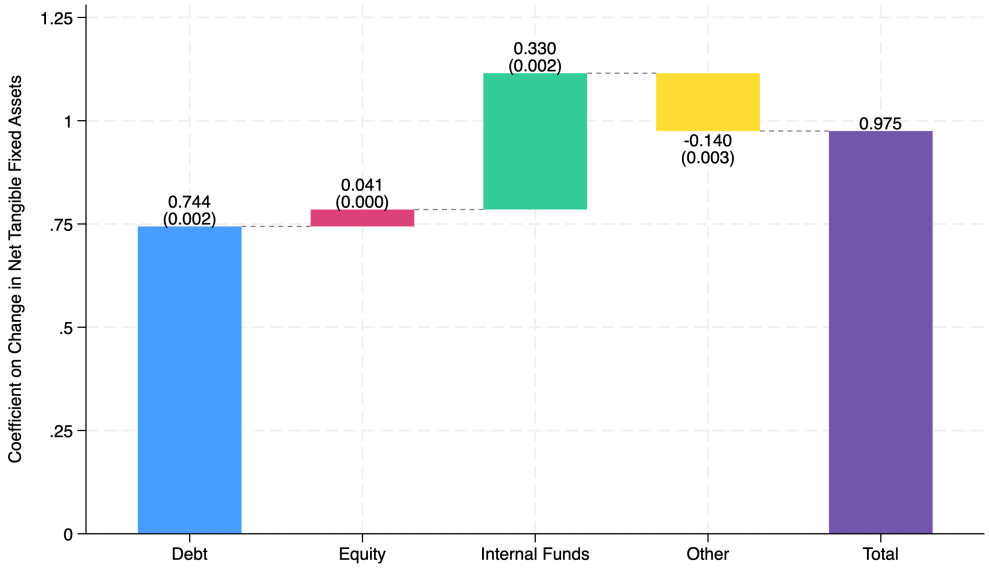
Figure C8: Firms' Capital Intensity Relative to 2010 Allowing for Firm Exit



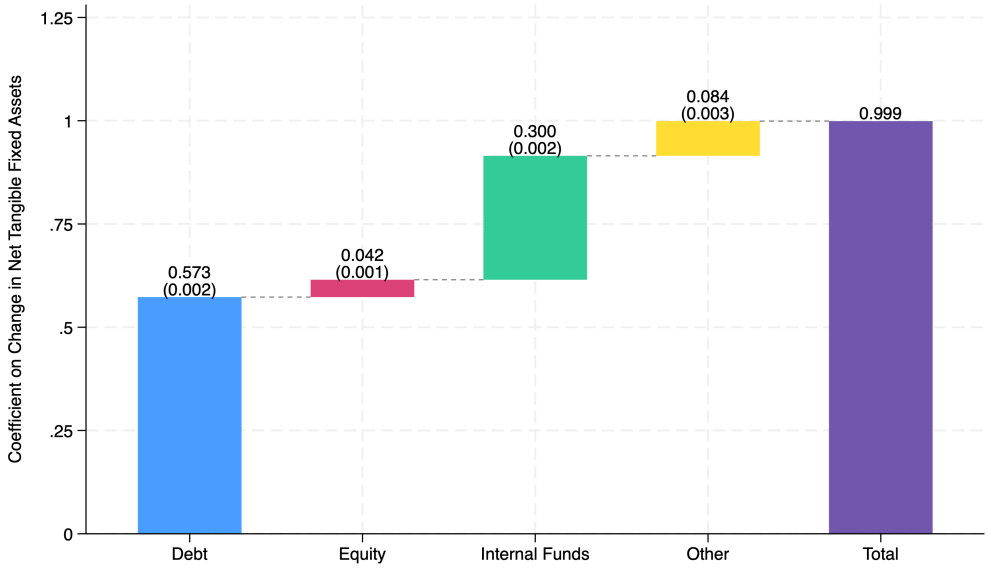
Sources: Moody's DataHub.
Notes: This figure describes the evolution of German firms' net tangible fixed assets per employee from 2007 to 2019, both their aggregate dynamics (i.e., of the total net tangible fixed assets per employee across all firms) and the differences between initially high- and low-leverage firms, while allowing for firm exit. Firms are included as long as both the numerator and denominator of the ratio are available in every year from 2007 to 2010, in contrast to Figure 2's requirement that they are available in all years. Firms' missing net tangible fixed assets and number of employees are interpolated between years until the year of their last observations, after which the firms are dropped from the analysis. Before dropping any firms due to their eventual exits, the top 1% of firms in terms of maximum size (i.e., number of employees) are excluded. The last two lines separate firms into two groups based on whether their mean ratio of long-term debt to total assets from 2007 to 2010 was above or below the median.

Figure C9: Variance Decomposition of Capital Investment across Firms—Robustness

(a) 1% Winsorization

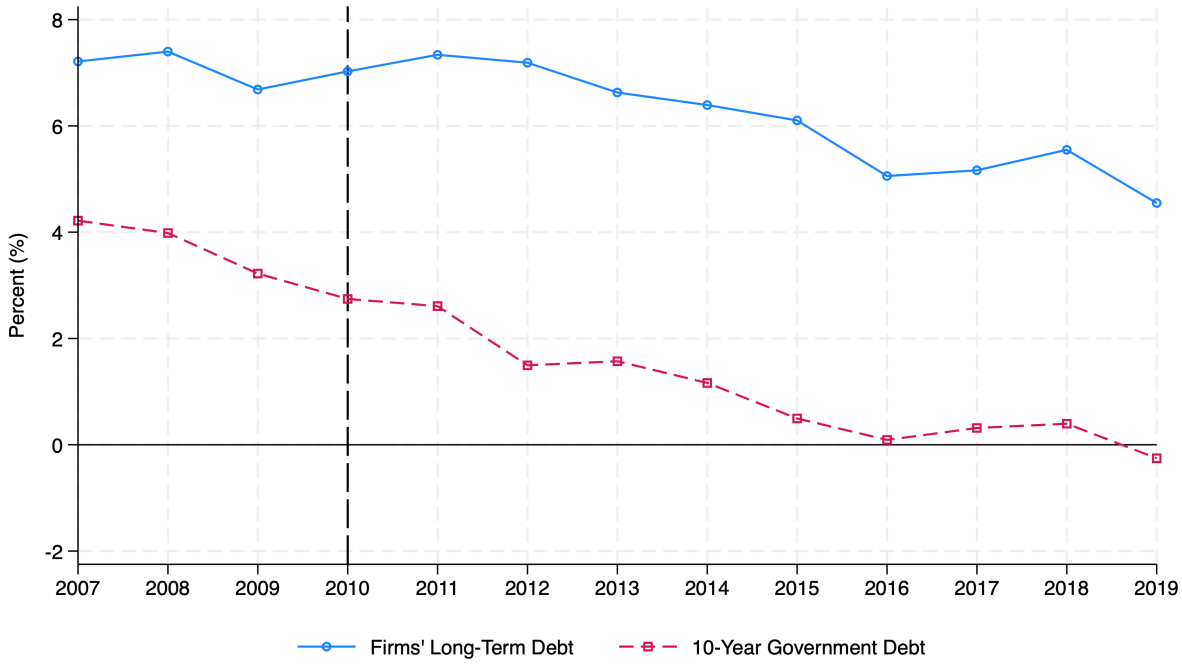


(b) 1% Winsorization and Weighting by 2010 Total Assets



Sources: Moody's DataHub.
Notes: This figure evaluates the robustness of Figure 3's variance decomposition of the change in net tangible fixed assets from 2010 to 2019 relative to total assets in 2010 across German firms, based on Equation (5) and restricting to firms whose net tangible fixed assets grew over this period. Panel (a) is based on a 1% winsorization. Panel (b) further weights each firm by its 2010 total assets. Each bar reflects the estimate from regressing its associated component on the change in net tangible fixed assets. Given the winsorization, the coefficients across components need not add up to 1. Debt refers to the change in long-term debt relative to initial total assets. Equity refers to the change in paid-in equity relative to initial total assets. Internal funds refers to the change in retained earnings minus the change in cash on hand relative to initial total assets. Other refers to the change in other liabilities minus the change in other assets relative to initial total assets.

Figure C10: Long-Term Interest Rates in Germany



Sources: Moody's DataHub; FRED.
Notes: This figure describes the evolution of the long-term interest rates paid by both German firms and the German government from 2007 to 2019. The first line plots the average interest rates paid across German firms, calculated as the total interest paid during each year across firms divided by their total long-term debt as of the previous year. Firms are included only if both the numerator and denominator of the ratio are available in all years. The second line plots the mean yield in each year on the 10-year government bond.

Table C3: Greater Sensitivity of Initially Higher-Leverage Firms' Borrowing Costs

	Change in Log Average Interest Rate		
	(1)	(2)	(3)
$H_{j0} \times d \ln D_j$	0.382^{***}		
	(0.055)		
By sector:			
× Manufacturing		0.267^{***}	
		(0.099)	
× Low-skill sectors		0.296^{***}	
		(0.086)	
× High-skill sectors		0.587^{***}	
		(0.102)	
By cohort:			
× Founded after 2000			0.245^{**}
			(0.114)
× Founded from 1996 to 2000			0.360^{***}
			(0.136)
× Founded in or before 1995			0.461^{***}
			(0.069)
No. firms	5,821	5,821	5,821

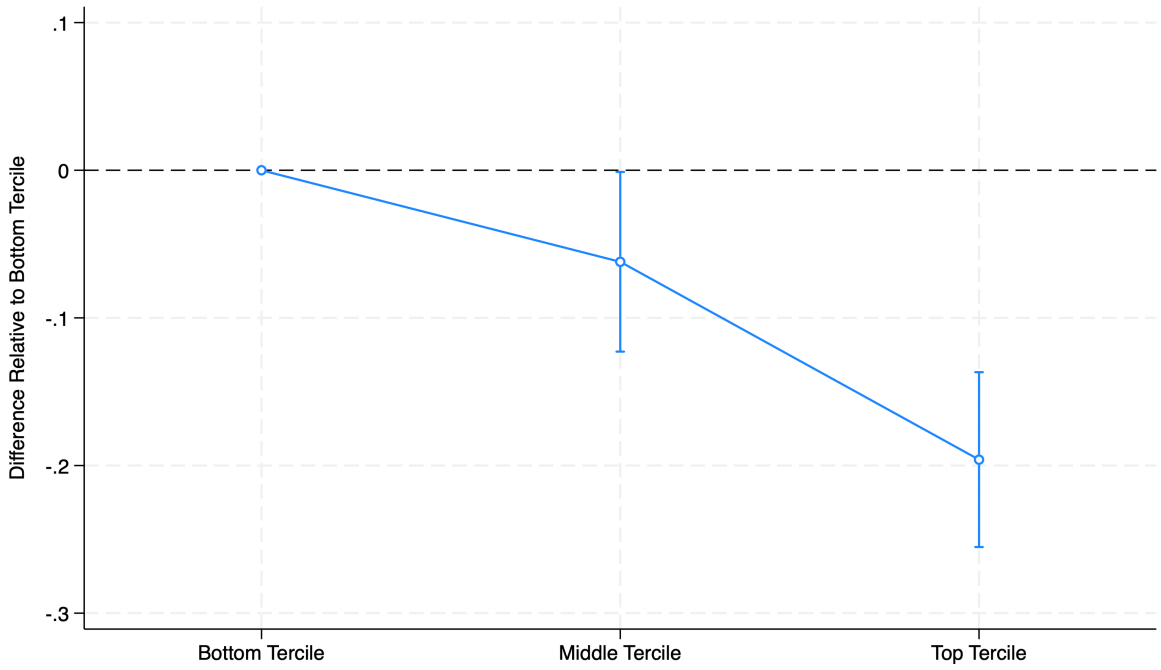
Sources: Moody's DataHub.
Notes: This table reports estimates of Equation (6), focusing on the coefficient δ on the interaction term $H_{j0}\ d \ln D_j$, and after applying a 1% winsorization. Column (1) is based on a regression of the change in log interest rates $d \ln r_j$ on the change in log debt $d \ln D_j$, the initially high-leverage dummy H_{j0}, and the interaction term. Column (2) further interacts all variables with a set of dummy variables for the manufacturing sector, low-skill sectors (accommodation and food services, construction, transportation and storage, administrative and support services, wholesale and retail trade, and other services), and high-skill sectors (all others listed in Appendix Table C2). Column (3) instead further interacts all variables with a set of dummy variables for cohorts founded after 2000, founded from 1996 to 2000, and founded in or before 1995. A firm's average interest rate is the ratio of its interest paid during a year to its long-term debt as of the previous year. The initially high-leverage dummy indicates whether the firm ranked in the upper half of the distribution of leverage across firms in 2010. Standard errors are robust to heteroskedasticity and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C4: Sensitivity of Firms' Borrowing Costs by Dimension of Heterogeneity

	Change in Log Average Interest Rate			
	(1)	(2)	(3)	(4)
$d \ln D_j$	-0.314^{***}	-0.411^{***}	-0.358^{***}	-0.369^{***}
	(0.025)	(0.033)	(0.043)	(0.057)
By leverage in 2010:				
× Middle tercile		0.322^{***}		
		(0.056)		
× Top tercile		0.534^{***}		
		(0.066)		
By sector:				
× Low-skill sectors			0.065	
			(0.059)	
× High-skill sectors			0.056	
			(0.062)	
By cohort:				
× Founded from 1996 to 2000				0.030
				(0.086)
× Founded in or before 1995				0.070
				(0.065)
No. firms	5,821	5,821	5,821	5,821

Sources: Moody's DataHub.
Notes: This table reports estimates of the heterogeneous sensitivity of firms' borrowing costs to additional borrowing along various dimensions of firm heterogeneity, after applying a 1% winsorization. Column (1) is based on a regression of the change in log interest rates $d \ln r_j$ on the change in log debt $d \ln D_j$. Column (2) adds as regressors a set of dummy variables for the bottom, middle, and top terciles of the 2010 leverage distribution and an interaction of $d \ln D_j$ with the dummies for the middle and top terciles. Column (3) instead adds a set of dummy variables for the manufacturing sector, low-skill sectors (accommodation and food services, construction, transportation and storage, administrative and support services, wholesale and retail trade, and other services), and high-skill sectors (all others listed in Appendix Table C2) and an interaction of $d \ln D_j$ with the dummies for the low-skill and high-skill sectors. Column (4) instead adds a set of dummy variables for cohorts founded after 2000, founded from 1996 to 2000, and founded in or before 1995 and an interaction of $d \ln D_j$ with the dummies for the two older cohorts. In columns (2)–(4), the coefficient on $d \ln D_j$ is therefore the slope for the bottom leverage tercile, manufacturing sector, and cohort founded after 2000, respectively, and the coefficients on the interactions are differences relative to these groups. A firm's average interest rate is the ratio of its interest paid during a year to its long-term debt as of the previous year. Standard errors are robust to heteroskedasticity and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

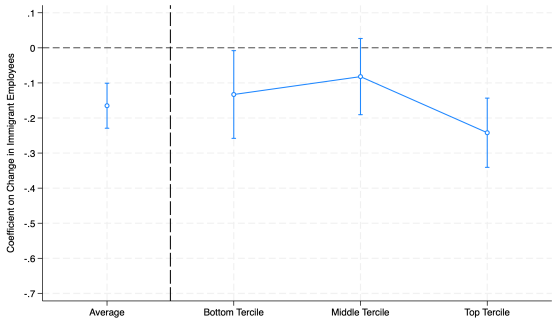
Figure C11: Differences in the Sensitivity of Capital Intensity to Immigrant Hiring by Initial Leverage



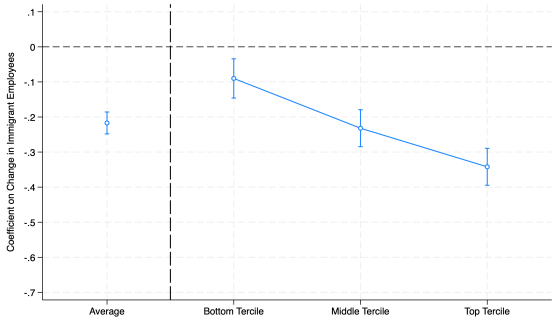
Sources: Custom link between Moody's DataHub and Establishment History Panel.
Notes: This figure plots the differences between the estimates of Equation (7) for initially higher-leverage firms and those for the initially lowest-leverage firms, regressing a firm's change in log net tangible fixed assets per employee from 2010 to 2019 on the change in its number of immigrant employees relative to its total number of employees in 2010, interacted with the tercile of the 2010 leverage distribution that the firm belongs to. The bottom tercile is the omitted category, so its difference is zero by construction. The figure plots 90% confidence intervals robust to heteroskedasticity.

Figure C12: Sensitivity of Capital Intensity to Immigrant Hiring by Initial Leverage within Sector Categories

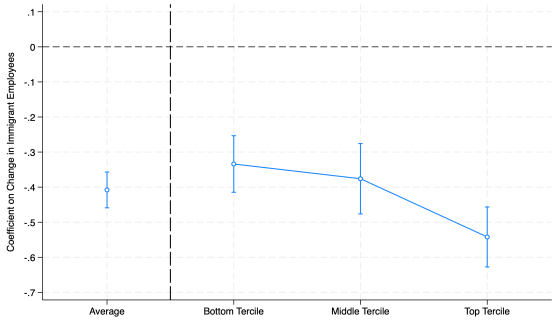
(a) Manufacturing



(b) Low-Skill Sectors



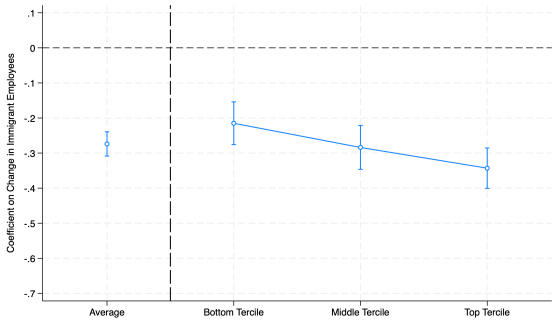
(c) High-Skill Sectors



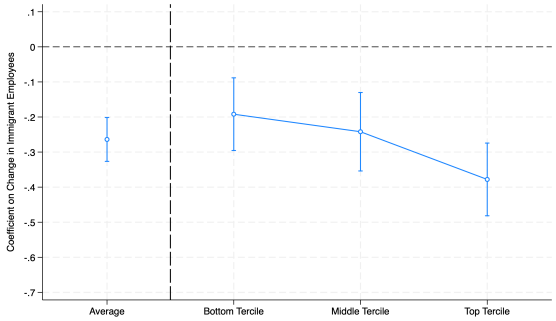
Sources: Custom link between Moody's DataHub and Establishment History Panel.
Notes: This figure plots estimates of Equation (7) separately within each sector category, regressing a firm's change in log net tangible fixed assets per employee from 2010 to 2019 on the change in its number of immigrant employees relative to its total number of employees in 2010, interacted with both its sector category and the tercile of the 2010 leverage distribution that the firm belongs to. Panel (a) considers firms in manufacturing. Panel (b) considers firms in low-skill sectors (accommodation and food services, construction, transportation and storage, administrative and support services, wholesale and retail trade, and other services). Panel (c) considers firms in high-skill sectors (all others listed in Appendix Table C2). In each panel, the first estimate for all firms in the sector category is from a version of Equation (7) interacted only with sector categories. The figure plots 90% confidence intervals robust to heteroskedasticity.

Figure C13: Sensitivity of Capital Intensity to Immigrant Hiring by Initial Leverage within Cohorts

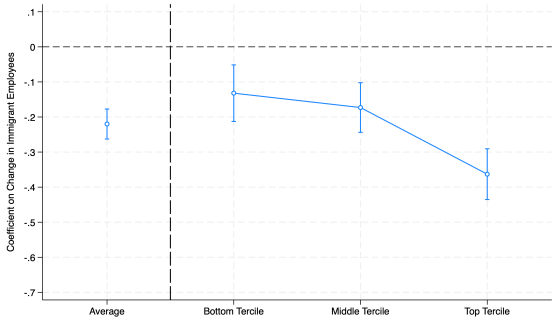
(a) Founded after 2000



(b) Founded from 1996 to 2000



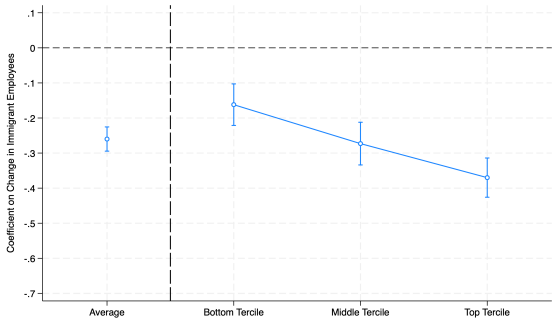
(c) Founded in or before 1995



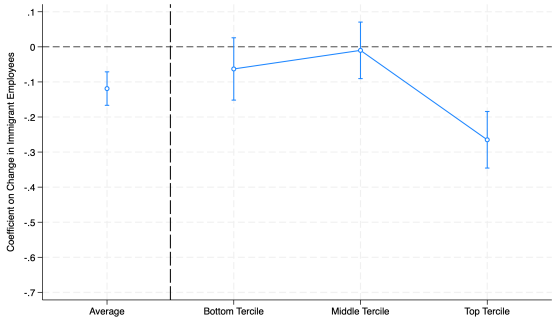
Sources: Custom link between Moody's DataHub and Establishment History Panel.
Notes: This figure plots estimates of Equation (7) separately within each cohort, regressing a firm's change in log net tangible fixed assets per employee from 2010 to 2019 on the change in its number of immigrant employees relative to its total number of employees in 2010, interacted with both its cohort and the tercile of the 2010 leverage distribution that the firm belongs to. Panel (a) considers firms founded after 2000. Panel (b) considers firms founded from 1996 to 2000. Panel (c) considers firms founded in or before 1995. A firm's cohort is based on enterprise-level data from Moody's DataHub. In each panel, the first estimate for all firms in the cohort is from a version of Equation (7) interacted only with cohorts. The figure plots 90% confidence intervals robust to heteroskedasticity.

Figure C14: Sensitivity of Capital Intensity to Immigrant Hiring by Initial Leverage within Size Terciles

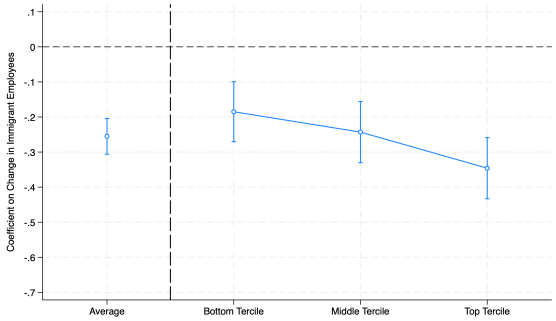
(a) Bottom Size Tercile



(b) Middle Size Tercile



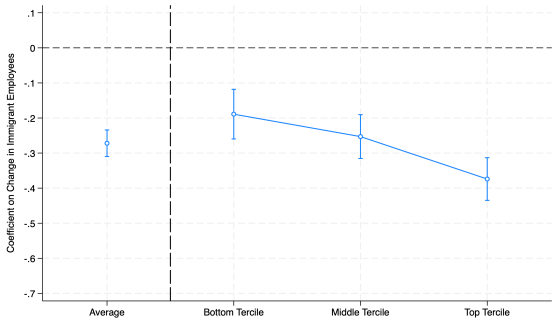
(c) Top Size Tercile



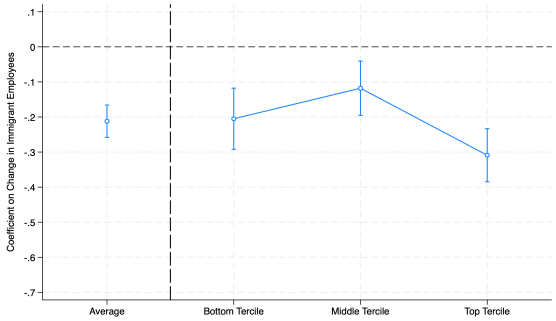
Sources: Custom link between Moody's DataHub and Establishment History Panel.
Notes: This figure plots estimates of Equation (7) separately within each tercile of the 2010 size distribution, regressing a firm's change in log net tangible fixed assets per employee from 2010 to 2019 on the change in its number of immigrant employees relative to its total number of employees in 2010, interacted with both its size tercile and the tercile of the 2010 leverage distribution that the firm belongs to. Panels (a), (b), and (c) consider firms in the bottom, middle, and top size terciles, respectively. A firm's size refers to its number of employees in 2010, based on the aggregated establishment-level social security records from the Establishment History Panel. In each panel, the first estimate for all firms in the size tercile is from a version of Equation (7) interacted only with size terciles. The figure plots 90% confidence intervals robust to heteroskedasticity.

Figure C15: Sensitivity of Capital Intensity to Immigrant Hiring by Initial Leverage within Skill Intensity Terciles

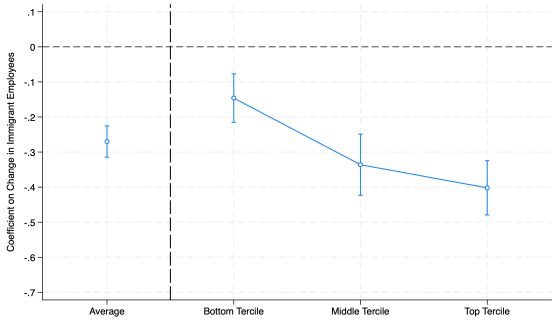
(a) Bottom Skill Intensity Tercile



(b) Middle Skill Intensity Tercile



(c) Top Skill Intensity Tercile



Sources: Custom link between Moody's DataHub and Establishment History Panel.
Notes: This figure plots estimates of Equation (7) separately within each tercile of the 2010 skill intensity distribution, regressing a firm's change in log net tangible fixed assets per employee from 2010 to 2019 on the change in its number of immigrant employees relative to its total number of employees in 2010, interacted with both its skill intensity tercile and the tercile of the 2010 leverage distribution that the firm belongs to. Panels (a), (b), and (c) consider firms in the bottom, middle, and top skill intensity terciles, respectively. A firm's skill intensity refers to the university-educated share of its employees in 2010, based on the aggregated establishment-level social security records from the Establishment History Panel. In each panel, the first estimate for all firms in the skill intensity tercile is from a version of Equation (7) interacted only with skill intensity terciles. The figure plots 90% confidence intervals robust to heteroskedasticity.

Appendix D: Econometric Approach

D.1 Derivation of Rotemberg Weights

Stack the observations across commuting zones r, and let $s_o^{\perp}$ and $dX^{\perp}$ denote the vectors of origin country o's local shares $s_{r,o}$ and of the endogenous regressor dX_r, respectively, after partialing out the controls W_r. Goldsmith-Pinkham et al. (2020) show that the SSIV estimator can be written as $\hat{\beta}^{SSIV} = \sum_o \alpha_o^{SSIV} \hat{\beta}_o$, where $\hat{\beta}_o$ is the just-identified IV estimator that uses $s_o^{\perp}$ as the instrument, and the Rotemberg weights are:

$$\alpha_o^{SSIV} = \frac{g_o \, s_o^{\perp\prime} dX^{\perp}}{\sum_{o'} g_{o'} \, s_{o'}^{\perp\prime} dX^{\perp}} \tag{B4}$$

The regression of $dX^{\perp}$ on $s_o^{\perp}$ yields the first-stage coefficient and R^2:

$$\hat{\pi}_o = \frac{s_o^{\perp\prime} dX^{\perp}}{s_o^{\perp\prime} s_o^{\perp}} \qquad \text{and} \qquad \hat{R}_o^2 = \frac{\left(s_o^{\perp\prime} dX^{\perp}\right)^2}{\left(s_o^{\perp\prime} s_o^{\perp}\right)\left(dX^{\perp\prime} dX^{\perp}\right)} = \hat{\pi}_o \frac{s_o^{\perp\prime} dX^{\perp}}{dX^{\perp\prime} dX^{\perp}}$$

so that:

$$s_o^{\perp\prime} dX^{\perp} = \frac{\hat{R}_o^2}{\hat{\pi}_o} dX^{\perp\prime} dX^{\perp} \tag{B5}$$

Inserting Equation (B5) into Equation (B4), the common factor $dX^{\perp\prime} dX^{\perp}$ cancels, yielding Equation (11):

$$\alpha_o^{SSIV} = \frac{\frac{g_o \hat{R}_o^2}{\hat{\pi}_o}}{\sum_{o'} \frac{g_{o'} \hat{R}_{o'}^2}{\hat{\pi}_{o'}}}$$

Similarly, Goldsmith-Pinkham et al. (2020) show that the TSLS estimator that uses all shares $s_o^{\perp}$ as separate instruments assigns the Rotemberg weights:

$$\alpha_o^{TSLS} = \frac{\tilde{\pi}_o \, s_o^{\perp\prime} dX^{\perp}}{\sum_{o'} \tilde{\pi}_{o'} \, s_{o'}^{\perp\prime} dX^{\perp}} \tag{B6}$$

where $\tilde{\pi}_o$ is the coefficient on $s_o^{\perp}$ in the first-stage regression of $dX^{\perp}$ on all shares jointly. If the covariance structure of the shares is ignored, i.e., the shares are treated as mutually orthogonal, then $\tilde{\pi}_o = \hat{\pi}_o$. Inserting Equation (B5) into Equation (B6), the first-stage coefficients cancel, yielding Equation (12):

$$\alpha_o^{TSLS} = \frac{\hat{R}_o^2}{\sum_{o'} \hat{R}_{o'}^2}$$

D.2 Additional Results

Table D1: *J*-Tests for the Effect of Immigration on Total Employment

	Valid under Homoskedasticity and Heteroskedasticity				Valid only under Homoskedasticity	
	HLIM	HFUL	EGMM	CUE	TSLS	LIML
	(1)	(2)	(3)	(4)	(5)	(6)
J-test *p*-value	0.321	0.318	0.571	0.650	0.073*	0.000***
No. commuting zones	117	117	117	117	117	117

Sources: Sample of Integrated Labour Market Biographies.
Notes: This table reports the *p*-values from *J*-tests for the commuting zone-level effect of immigration from 2010 to 2019 on total employment, based on different overidentified estimators of Equation (8) that use as instruments the 74 origin country-specific shares of local employment included in the construction of the ethnic-enclave shift-share instrument defined by Equation (9). Column (1) considers the heteroskedasticity-robust limited information maximum likelihood estimator (HLIM). Column (2) considers the heteroskedasticity-robust Fuller estimator (HFUL). Column (3) considers the two-step efficient generalized method of moments estimator (EGMM). Column (4) considers the continuously updating generalized method of moments estimator (CUE). Column (5) considers the two-stage least squares estimator (TSLS). Column (6) considers the limited information maximum likelihood estimator (LIML). All columns control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. Commuting zones are weighted by their 2010 shares of nationwide employment. The tests in columns (1)–(4) are robust to heteroskedasticity, while those in columns (5)–(6) assume homoskedasticity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table D2: Overidentified Estimates of the Effect of Immigration on Total Employment

	Change in Total Employment Relative to Initial Total Employment				
	SSIV	RSSIV	HLIM	HFUL	LIML
	(1)	(2)	(3)	(4)	(5)
Change in immigrant employment relative to initial total employment	0.172	0.603**	0.453	0.528	0.502**
	(0.469)	(0.280)	(0.509)	(0.447)	(0.221)
No. commuting zones	117	117	117	117	117

Sources: Sample of Integrated Labour Market Biographies.
Notes: This table reports estimates of the commuting zone-level effect of immigration from 2010 to 2019 on total employment, based on different overidentified estimators of Equation (8) that use as instruments the 74 origin country-specific shares of local employment included in the construction of the ethnic-enclave shift-share instrument defined by Equation (9). Column (1) considers the shift-share instrumental variable estimator (SSIV) based on the ethnic-enclave shift-share instrument defined in Equation (9). Column (2) considers the reweighted shift-share instrumental variable estimator (RSSIV) based on the modified ethnic-enclave shift-share instrument defined in Equation (13). Column (3) considers the heteroskedasticity-robust limited information maximum likelihood estimator (HLIM). Column (4) considers the heteroskedasticity-robust Fuller estimator (HFUL). Column (5) considers the limited information maximum likelihood estimator (LIML). All columns control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. Commuting zones are weighted by their 2010 shares of nationwide employment. Standard errors are robust to heteroskedasticity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

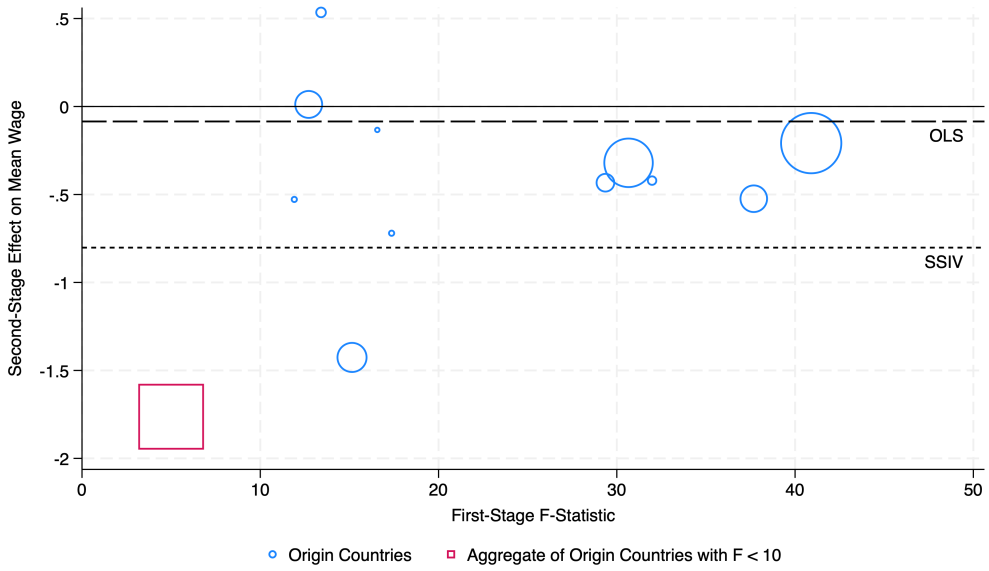
Table D3: Commuting Zone-Level Effects of Immigration: Alternative Weights

	Relative Change in Total Employment		Change in Mean Log Wage	
	RSSIV	RSIV	RSSIV	RSIV
	(1)	(2)	(3)	(4)
Change in immigrant employment relative to initial total employment	0.603**	0.558**	−0.337*	−0.547***
	(0.280)	(0.261)	(0.173)	(0.176)
First-stage F-statistic	50.89	79.82	50.89	79.82
First-stage partial R^2	0.408	0.484	0.408	0.484
No. commuting zones	117	117	117	117

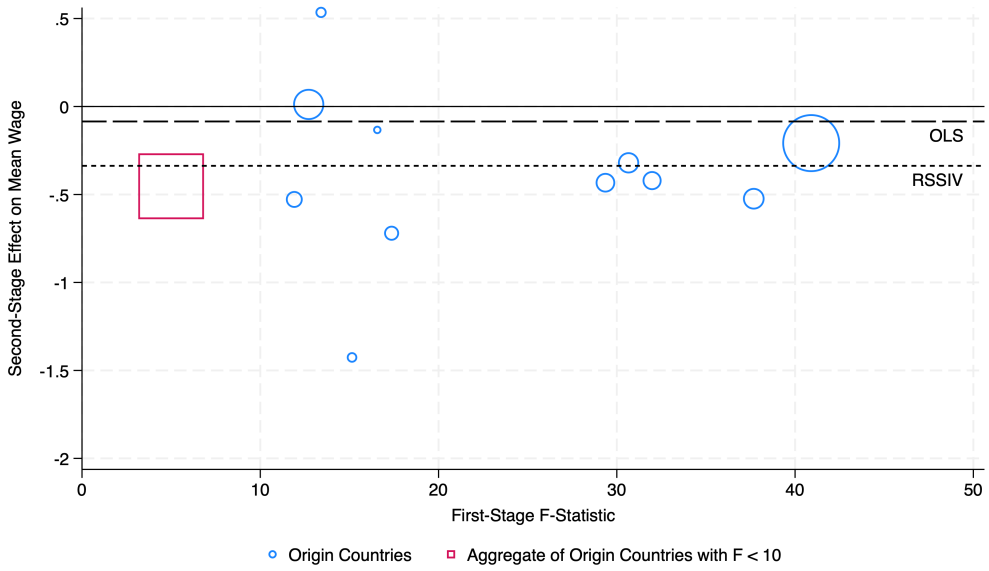
Sources: Sample of Integrated Labour Market Biographies.
Notes: This table reports estimates of the commuting zone-level effect of immigration from 2010 to 2019 on total employment and mean wages, using as instruments alternative weighted sums of 74 origin country-specific shares of local employment. The outcome variable in columns (1) and (2) is the change in commuting zone-level total employment from 2010 to 2019 relative to initial total employment in 2010. The outcome variable in columns (3) and (4) is the change in the mean log wage of full-time employees from 2010 to 2019. Columns (1) and (3) are based on the reweighted shift-share instrumental variable estimator (RSSIV) using the instrument defined in Equation (13). Columns (2) and (4) are based on the reweighted share instrumental variable estimator (RSIV) using the instrument defined in Equation (15). All columns control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. Commuting zones are weighted by their 2010 shares of nationwide employment. Standard errors are robust to heteroskedasticity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure D1: Visual Tests for the Effect of Immigration on Mean Wages

(a) Shift-Share Instrumental Variable Estimator

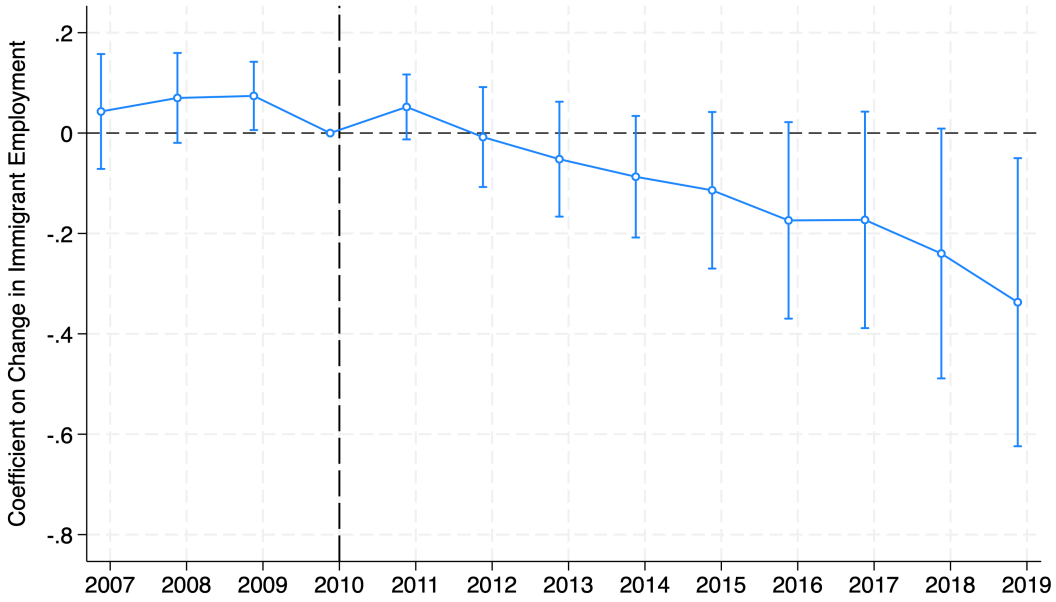


(b) Reweighted Shift-Share Instrumental Variable Estimator



Sources: Sample of Integrated Labour Market Biographies.
Notes: This figure plots the visual overidentification test recommended by Goldsmith-Pinkham et al. (2020). Panel (a) illustrates the plot for the shift-share instrumental variable estimator (SSIV) based on the instrument defined in Equation (9). Panel (b) illustrates the plot for the reweighted shift-share instrumental variable estimator (RSSIV) based on the instrument defined in Equation (13). The vertical axis plots the second-stage estimate based on the just-identified estimator for each origin country-specific share $s_{r,o}$. The horizontal axis plots the corresponding first-stage F-statistic for that estimator. Each point is sized by the weight assigned to it by the corresponding estimator. Circles indicate individual origin countries, none of which is assigned a negative weight. The square indicates the estimate from aggregating across shares with first-stage F-statistics below 10. Each panel plots the resulting weighted average across just-identified estimates as well as the ordinary least squares estimate (OLS).

Figure D2: Dynamic Effects of Immigration from 2010 to 2019 on Mean Wages



Sources: Sample of Integrated Labour Market Biographies.
Notes: This figure plots instrumental variable estimates of the commuting zone-level effects of immigration from 2010 to 2019 on the change in the mean log wage from 2010 to each year, based on Equation (8) and the reweighted ethnic-enclave shift-share instrument defined in Equation (13). The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. Commuting zones are weighted by their 2010 shares of nationwide employment. The figure plots 90% confidence intervals robust to heteroskedasticity.

Appendix E: Firm-Level Effects of Immigration

Table E1: Heterogeneous Effects of Immigration from 2010 to 2019 on Firm-Level Immigrant Hiring by Sector Category

	Change in Immigrant Employees Relative to Initial Total Employees		
	(1)	(2)	(3)
Local immigration $dX_{r(j)}$	1.124***		0.981***
	(0.131)		(0.129)
By sector:			
× Manufacturing		0.981***	
		(0.129)	
× Low-skill sectors		1.220***	0.239***
		(0.139)	(0.050)
× High-skill sectors		1.009***	0.028
		(0.125)	(0.066)
No. commuting zones	117	117	117
No. firms	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 on firm-level immigrant hiring by sector category, based on the regression specified in Equation (16), instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted ethnic-enclave shift-share instrument defined in Equation (13), and interacting both $dX_{r(j)}$ and the instrument with dummies for manufacturing, low-skill sectors, and high-skill sectors. Low-skill sectors refer to accommodation and food services, construction, transportation and storage, administrative and support services, wholesale and retail trade, and other services. High-skill sectors refer to all others listed in Appendix Table C2. All columns consider as the outcome variable the change in the firm's number of immigrant employees from 2010 to 2019 relative to its total number of employees in 2010. Column (1) considers the average effect based on the version of Equation (16) without the interaction. Column (2) excludes the uninteracted terms and includes interactions for the sector categories. Column (3) includes the uninteracted terms and interactions for the low-skill and high-skill sectors, so the coefficients on these interactions are differences relative to the manufacturing sector. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table E2: Heterogeneous Effects of Immigration from 2010 to 2019 on Firm-Level Immigrant Hiring by Cohort

	Change in Immigrant Employees Relative to Initial Total Employees		
	(1)	(2)	(3)
Local immigration $dX_{r(j)}$	1.124***		1.533***
	(0.131)		(0.167)
By cohort:			
× Founded after 2000		1.533***	
		(0.167)	
× Founded from 1996 to 2000		1.177***	−0.356***
		(0.157)	(0.107)
× Founded in or before 1995		0.949***	−0.584***
		(0.134)	(0.087)
No. commuting zones	117	117	117
No. firms	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 on firm-level immigrant hiring by cohort, based on the regression specified in Equation (16), instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted ethnic-enclave shift-share instrument defined in Equation (13), and interacting both $dX_{r(j)}$ and the instrument with dummies for cohorts founded after 2000, founded from 1996 to 2000, and founded in or before 1995. All columns consider as the outcome variable the change in the firm's number of immigrant employees from 2010 to 2019 relative to its total number of employees in 2010. Column (1) considers the average effect based on the version of Equation (16) without the interaction. Column (2) excludes the uninteracted terms and includes interactions for the different cohorts. Column (3) includes the uninteracted terms and interactions for the cohorts founded from 1996 to 2000 and in or before 1995, so the coefficients on these interactions are differences relative to the cohort founded after 2000. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table E3: Heterogeneous Effects of Immigration from 2010 to 2019 on Firm-Level Immigrant Hiring by Initial Size

	Change in Immigrant Employees Relative to Initial Total Employees		
	(1)	(2)	(3)
Local immigration $dX_{r(j)}$	1.124^{***}		1.488^{***}
	(0.131)		(0.148)
By size in 2010:			
× Bottom tercile		1.488^{***}	
		(0.148)	
× Middle tercile		1.140^{***}	-0.348^{***}
		(0.127)	(0.073)
× Top tercile		1.075^{***}	-0.413^{***}
		(0.134)	(0.061)
No. commuting zones	117	117	117
No. firms	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 on firm-level immigrant hiring by initial size, based on the regression specified in Equation (16), instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted ethnic-enclave shift-share instrument defined in Equation (13), and interacting both $dX_{r(j)}$ and the instrument with dummies for the tercile of the 2010 size distribution that firm j belonged to. Size refers to the firm's number of employees. All columns consider as the outcome variable the change in the firm's number of immigrant employees from 2010 to 2019 relative to its total number of employees in 2010. Column (1) considers the average effect based on the version of Equation (16) without the interaction. Column (2) excludes the uninteracted terms and includes interactions for the bottom, middle, and top terciles. Column (3) includes the uninteracted terms and interactions for the middle and top terciles, so the coefficients on these interactions are differences relative to the bottom tercile. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table E4: Heterogeneous Effects of Immigration from 2010 to 2019 on Firm-Level Immigrant Hiring by Initial Skill Intensity

	Change in Immigrant Employees Relative to Initial Total Employees		
	(1)	(2)	(3)
Local immigration $dX_{r(j)}$	1.124***		1.271***
	(0.131)		(0.127)
By skill intensity in 2010:			
× Bottom tercile		1.271***	
		(0.127)	
× Middle tercile		1.206***	−0.064
		(0.138)	(0.067)
× Top tercile		0.925***	−0.345***
		(0.127)	(0.065)
No. commuting zones	117	117	117
No. firms	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 on firm-level immigrant hiring by initial skill intensity, based on the regression specified in Equation (16), instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted ethnic-enclave shift-share instrument defined in Equation (13), and interacting both $dX_{r(j)}$ and the instrument with dummies for the tercile of the 2010 skill intensity distribution that firm j belonged to. Skill intensity refers to the university-educated share of the firm's employees. All columns consider as the outcome variable the change in the firm's number of immigrant employees from 2010 to 2019 relative to its total number of employees in 2010. Column (1) considers the average effect based on the version of Equation (16) without the interaction. Column (2) excludes the uninteracted terms and includes interactions for the bottom, middle, and top terciles. Column (3) includes the uninteracted terms and interactions for the middle and top terciles, so the coefficients on these interactions are differences relative to the bottom tercile. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table E5: Average Firm-Level Effects of Immigration—Alternative Reweighting

	Immigrant Employees (1)	Log Capital per Employee (2)	Log Mean Wage (3)	Native Employees (4)
Local immigration $dX_{r(j)}$	1.073***	−0.867**	−0.384***	−0.231
	(0.113)	(0.354)	(0.115)	(0.171)
No. commuting zones	117	117	117	117
No. firms	140,973	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the average firm-level effect of immigration from 2010 to 2019, based on the regression specified in Equation (16) and instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted share instrument defined in Equation (15). Column (1) considers as the outcome variable the change in firm j's number of immigrant employees from 2010 to 2019 relative to its total number of employees in 2010. Column (2) considers the change in the firm's log net tangible fixed assets per employee from 2010 to 2019. Column (3) considers the change in the log mean wage of its full-time employees from 2010 to 2019. Column (4) considers the change in its number of native employees from 2010 to 2019 relative to its total number of employees in 2010. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table E6: Heterogeneous Effects of Immigration from 2010 to 2019 on Firm-Level Immigrant Hiring by Initial Leverage—Alternative Reweighting

	Change in Immigrant Employees Relative to Initial Total Employees		
	(1)	(2)	(3)
Local immigration $dX_{r(j)}$	1.073^{***}		1.117^{***}
	(0.113)		(0.132)
By leverage in 2010:			
× Bottom tercile		1.117^{***}	
		(0.132)	
× Middle tercile		1.021^{***}	-0.097
		(0.117)	(0.069)
× Top tercile		1.073^{***}	-0.044
		(0.108)	(0.089)
No. commuting zones	117	117	117
No. firms	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 on firm-level immigrant hiring by initial leverage, based on the regression specified in Equation (16), instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted share instrument defined in Equation (15), and interacting both $dX_{r(j)}$ and the instrument with dummies for the tercile of the 2010 leverage distribution that firm j belonged to. All columns consider as the outcome variable the change in the firm's number of immigrant employees from 2010 to 2019 relative to its total number of employees in 2010. Column (1) considers the average effect based on the version of Equation (16) without the interaction. Column (2) excludes the uninteracted terms and includes interactions for the bottom, middle, and top terciles. Column (3) includes the uninteracted terms and interactions for the middle and top terciles, so the coefficients on these interactions are differences relative to the bottom tercile. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table E7: Heterogeneous Effects of Immigration from 2010 to 2019 on Firm-Level Capital Intensity by Initial Leverage—Alternative Reweighting

	Change in Log Net Tangible Fixed Assets per Employee		
	(1)	(2)	(3)
Local immigration $dX_{r(j)}$	-0.867^{**}		-0.606
	(0.354)		(0.384)
By leverage in 2010:			
× Bottom tercile		-0.606	
		(0.384)	
× Middle tercile		-0.739^{*}	-0.133
		(0.426)	(0.351)
× Top tercile		-1.364^{***}	-0.759
		(0.495)	(0.499)
No. commuting zones	117	117	117
No. firms	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 on firm-level capital intensity by initial leverage, based on the regression specified in Equation (16), instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted share instrument defined in Equation (15), and interacting both $dX_{r(j)}$ and the instrument with dummies for the tercile of the 2010 leverage distribution that firm j belonged to. All columns consider as the outcome variable the change in the firm's log net tangible fixed assets per employee from 2010 to 2019. Column (1) considers the average effect based on the version of Equation (16) without the interaction. Column (2) excludes the uninteracted terms and includes interactions for the bottom, middle, and top terciles. Column (3) includes the uninteracted terms and interactions for the middle and top terciles, so the coefficients on these interactions are differences relative to the bottom tercile. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table E8: Heterogeneous Effects of Immigration from 2010 to 2019 on Firm-Level Borrowing by Initial Leverage—Alternative Reweighting

	Symmetric Growth Rate of Long-Term Debt		
	(1)	(2)	(3)
Local immigration $dX_{r(j)}$	0.151		1.351**
	(0.378)		(0.625)
By leverage in 2010:			
× Bottom tercile		1.351**	
		(0.625)	
× Middle tercile		−0.781*	−2.132***
		(0.423)	(0.633)
× Top tercile		−0.383	−1.734***
		(0.379)	(0.649)
No. commuting zones	117	117	117
No. firms	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 on firm-level borrowing by initial leverage, based on the regression specified in Equation (16), instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted share instrument defined in Equation (15), and interacting both $dX_{r(j)}$ and the instrument with dummies for the tercile of the 2010 leverage distribution that firm j belonged to. All columns consider as the outcome variable the symmetric growth rate of the firm's long-term debt from 2010 to 2019. Column (1) considers the average effect based on the version of Equation (16) without the interaction. Column (2) excludes the uninteracted terms and includes interactions for the bottom, middle, and top terciles. Column (3) includes the uninteracted terms and interactions for the middle and top terciles, so the coefficients on these interactions are differences relative to the bottom tercile. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table E9: Heterogeneous Effects of Immigration from 2010 to 2019 on Firm-Level Wages by Initial Leverage—Alternative Reweighting

	Change in Log Mean Wage of Full-Time Employees		
	(1)	(2)	(3)
Local immigration $dX_{r(j)}$	-0.384^{***}		-0.291^{**}
	(0.115)		(0.114)
By leverage in 2010:			
× Bottom tercile		-0.291^{**}	
		(0.114)	
× Middle tercile		-0.400^{***}	-0.109
		(0.121)	(0.072)
× Top tercile		-0.489^{***}	-0.197^{***}
		(0.131)	(0.072)
No. commuting zones	117	117	117
No. firms	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 on firm-level wages by initial leverage, based on the regression specified in Equation (16), instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted share instrument defined in Equation (15), and interacting both $dX_{r(j)}$ and the instrument with dummies for the tercile of the 2010 leverage distribution that firm j belonged to. All columns consider as the outcome variable the change in the log mean wage of the firm's full-time employees from 2010 to 2019. Column (1) considers the average effect based on the version of Equation (16) without the interaction. Column (2) excludes the uninteracted terms and includes interactions for the bottom, middle, and top terciles. Column (3) includes the uninteracted terms and interactions for the middle and top terciles, so the coefficients on these interactions are differences relative to the bottom tercile. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table E10: Heterogeneous Effects of Immigration from 2010 to 2019 on Firm-Level Native Employment by Initial Leverage—Alternative Reweighting

	Change in Native Employees Relative to Initial Total Employees		
	(1)	(2)	(3)
Local immigration $dX_{r(j)}$	−0.231		−0.130
	(0.171)		(0.214)
By leverage in 2010:			
× Bottom tercile		−0.130	
		(0.214)	
× Middle tercile		−0.096	0.034
		(0.185)	(0.155)
× Top tercile		−0.522***	−0.391**
		(0.184)	(0.173)
No. commuting zones	117	117	117
No. firms	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 on firm-level native employment by initial leverage, based on the regression specified in Equation (16), instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted share instrument defined in Equation (15), and interacting both $dX_{r(j)}$ and the instrument with dummies for the tercile of the 2010 leverage distribution that firm j belonged to. All columns consider as the outcome variable the change in the firm's number of native employees from 2010 to 2019 relative to its total number of employees in 2010. Column (1) considers the average effect based on the version of Equation (16) without the interaction. Column (2) excludes the uninteracted terms and includes interactions for the bottom, middle, and top terciles. Column (3) includes the uninteracted terms and interactions for the middle and top terciles, so the coefficients on these interactions are differences relative to the bottom tercile. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table E11: Heterogeneous Effects of Immigration from 2010 to 2019 by Sector Category

	Log Capital Intensity (1)	Growth of Debt (2)	Log Mean Wage (3)	Native Employees (4)
Local immigration $dX_{r(j)}$ by sector:				
× Manufacturing	−0.221	0.379	−0.253*	−0.375*
	(0.352)	(0.506)	(0.135)	(0.212)
× Low-skill sectors	−0.684*	0.374	−0.212	−0.431**
	(0.407)	(0.524)	(0.143)	(0.182)
× High-skill sectors	−1.433***	−0.025	−0.293**	−0.429*
	(0.487)	(0.595)	(0.137)	(0.223)
No. commuting zones	117	117	117	117
No. firms	140,973	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 by sector category, interacting both $dX_{r(j)}$ and the instrument with dummies for the sector category of firm j, based on the regression specified in Equation (16) and instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted ethnic-enclave shift-share instrument defined in Equation (13). Column (1) considers as the outcome variable the change in firm j's log net tangible fixed assets per employee from 2010 to 2019. Column (2) considers the symmetric growth rate of its long-term debt from 2010 to 2019. Column (3) considers the change in the log mean wage of its full-time employees. Column (4) considers the change in its number of native employees relative to its total number of employees in 2010. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table E12: Heterogeneous Effects of Immigration from 2010 to 2019 by Cohort

	Log Capital Intensity (1)	Growth of Debt (2)	Log Mean Wage (3)	Native Employees (4)
Local immigration $dX_{r(j)}$ by cohort:				
× Founded 2001–2010	-1.498^{***}	-0.514	-0.416^{***}	-0.561^{**}
	(0.429)	(0.515)	(0.142)	(0.253)
× Founded 1996–2000	-1.033	-0.685	-0.172	-0.514^{**}
	(0.641)	(0.992)	(0.162)	(0.230)
× Founded 1995 or before	-0.355	0.856^{*}	-0.184	-0.337^{**}
	(0.383)	(0.460)	(0.134)	(0.162)
No. commuting zones	117	117	117	117
No. firms	140,973	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 by cohort, interacting both $dX_{r(j)}$ and the instrument with dummies for the cohort of firm j, based on the regression specified in Equation (16) and instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted ethnic-enclave shift-share instrument defined in Equation (13). Column (1) considers as the outcome variable the change in firm j's log net tangible fixed assets per employee from 2010 to 2019. Column (2) considers the symmetric growth rate of its long-term debt from 2010 to 2019. Column (3) considers the change in the log mean wage of its full-time employees. Column (4) considers the change in its number of native employees relative to its total number of employees in 2010. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table E13: Heterogeneous Effects of Immigration from 2010 to 2019 by Initial Size

	Log Capital Intensity (1)	Growth of Debt (2)	Log Mean Wage (3)	Native Employees (4)
Local immigration $dX_{r(j)}$ by size in 2010:				
× Bottom size tercile	-0.941^{***}	-0.402	-0.225^{*}	-0.718^{***}
	(0.347)	(0.393)	(0.128)	(0.214)
× Middle size tercile	-0.675^{**}	0.071	-0.265^{**}	-0.260
	(0.323)	(0.402)	(0.128)	(0.183)
× Top size tercile	-0.723^{*}	0.442	-0.231^{*}	-0.428^{**}
	(0.390)	(0.485)	(0.139)	(0.179)
No. commuting zones	117	117	117	117
No. firms	140,973	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 by initial size, interacting both $dX_{r(j)}$ and the instrument with dummies for the tercile of the 2010 size distribution that firm j belonged to, based on the regression specified in Equation (16) and instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted ethnic-enclave shift-share instrument defined in Equation (13). Column (1) considers as the outcome variable the change in firm j's log net tangible fixed assets per employee from 2010 to 2019. Column (2) considers the symmetric growth rate of its long-term debt from 2010 to 2019. Column (3) considers the change in the log mean wage of its full-time employees. Column (4) considers the change in its number of native employees relative to its total number of employees in 2010. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table E14: Heterogeneous Effects of Immigration from 2010 to 2019 by Initial Skill Intensity

	Log Capital Intensity (1)	Growth of Debt (2)	Log Mean Wage (3)	Native Employees (4)
Local immigration $dX_{r(j)}$ by skill intensity in 2010:				
× Bottom skill tercile	−0.131	−0.273	−0.176	−0.586***
	(0.449)	(0.400)	(0.133)	(0.189)
× Middle skill tercile	−0.500	0.624	−0.206	−0.569***
	(0.438)	(0.598)	(0.151)	(0.188)
× Top skill tercile	−1.388***	0.119	−0.317**	−0.109
	(0.404)	(0.474)	(0.129)	(0.194)
No. commuting zones	117	117	117	117
No. firms	140,973	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 by initial skill intensity, interacting both $dX_{r(j)}$ and the instrument with dummies for the tercile of the 2010 skill intensity distribution that firm j belonged to, based on the regression specified in Equation (16) and instrumenting the change in local immigrant employment relative to initial total employment $dX_{r(j)}$ with the reweighted ethnic-enclave shift-share instrument defined in Equation (13). Column (1) considers as the outcome variable the change in firm j's log net tangible fixed assets per employee from 2010 to 2019. Column (2) considers the symmetric growth rate of its long-term debt from 2010 to 2019. Column (3) considers the change in the log mean wage of its full-time employees. Column (4) considers the change in its number of native employees relative to its total number of employees in 2010. Commuting zones are weighted by their 2010 shares of nationwide employment based on the Sample of Integrated Labour Market Biographies (SIAB). Firms are weighted by their 2010 shares of the total number of employees in their commuting zone based on the Establishment History Panel. The estimates control for the ages 15–29, ages 30–49, university-educated, apprenticeship-trained, female, and manufacturing shares of employed natives in 1993. They also control for interactions of a firm's sector, cohort, and terciles in the distributions across firms of size, skill intensity, and leverage in 2010. Standard errors are clustered by commuting zone and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table E15: Heterogeneous Effects of Immigration from 2010 to 2019 on Firm-Level Immigrant Hiring by Initial Leverage and Other Dimensions of Heterogeneity

	Leverage Tercile in 2010			Top −
	Bottom	Middle	Top	Bottom
	(1)	(2)	(3)	(4)
Panel (a): By sector				
Manufacturing	0.955***	0.900***	1.123***	0.168*
	(0.144)	(0.136)	(0.145)	(0.086)
Low-skill sectors	1.357***	1.112***	1.159***	−0.199
	(0.158)	(0.158)	(0.143)	(0.121)
High-skill sectors	0.960***	1.069***	1.019***	0.059
	(0.156)	(0.146)	(0.202)	(0.258)
Panel (b): By cohort				
Founded after 2000	1.674***	1.371***	1.520***	−0.153
	(0.229)	(0.197)	(0.162)	(0.180)
Founded from 1996 to 2000	1.262***	1.211***	1.023***	−0.239
	(0.163)	(0.237)	(0.175)	(0.174)
Founded in or before 1995	0.978***	0.918***	0.949***	−0.029
	(0.146)	(0.151)	(0.138)	(0.101)
Panel (c): By size in 2010				
Bottom tercile	1.601***	1.282***	1.574***	−0.027
	(0.154)	(0.175)	(0.148)	(0.065)
Middle tercile	1.108***	1.221***	1.097***	−0.011
	(0.135)	(0.143)	(0.124)	(0.069)
Top tercile	1.161***	0.980***	1.066***	−0.095
	(0.151)	(0.148)	(0.135)	(0.114)
Panel (d): By skill intensity in 2010				
Bottom tercile	1.377***	1.193***	1.255***	−0.123
	(0.145)	(0.145)	(0.147)	(0.091)
Middle tercile	1.352***	1.097***	1.153***	−0.199
	(0.158)	(0.164)	(0.163)	(0.162)
Top tercile	0.923***	0.893***	0.971***	0.049
	(0.145)	(0.123)	(0.152)	(0.141)
No. commuting zones	117	117	117	117
No. firms	140,973	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 on the change in firm j's number of immigrant employees relative to its total number of employees in 2010, by the tercile of the 2010 leverage distribution that it belonged to, interacted with its category along one other dimension of firm heterogeneity at a time. Column (4) reports the difference between the top and bottom leverage terciles among firms in each category. See Appendix Table E14 for further details on the specification. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table E16: Heterogeneous Effects of Immigration from 2010 to 2019 by Initial Leverage and Sector Category

	Log Capital Intensity (1)	Growth of Debt (2)	Log Mean Wage (3)	Native Employees (4)
Manufacturing, by leverage in 2010:				
× Bottom tercile	−0.460	0.772	−0.171	−0.628**
	(0.423)	(1.043)	(0.142)	(0.278)
× Middle tercile	0.015	−0.099	−0.242	−0.118
	(0.469)	(0.619)	(0.149)	(0.274)
× Top tercile	−0.223	0.510	−0.374***	−0.399
	(0.626)	(0.685)	(0.137)	(0.252)
Top − bottom tercile	0.237	−0.262	−0.203***	0.229
	(0.707)	(1.290)	(0.075)	(0.310)
Low-skill sectors, by leverage in 2010:				
× Bottom tercile	−0.532	2.028**	−0.123	−0.110
	(0.469)	(0.889)	(0.158)	(0.213)
× Middle tercile	−0.849	−0.411	−0.196	−0.406*
	(0.603)	(0.584)	(0.158)	(0.215)
× Top tercile	−0.694	−0.918**	−0.347**	−0.874***
	(0.473)	(0.432)	(0.167)	(0.263)
Top − bottom tercile	−0.162	−2.946***	−0.223*	−0.764***
	(0.542)	(0.793)	(0.123)	(0.258)
High-skill sectors, by leverage in 2010:				
× Bottom tercile	−0.923	1.602*	−0.294*	−0.519*
	(0.751)	(0.943)	(0.159)	(0.311)
× Middle tercile	−1.367**	−1.971**	−0.318*	0.071
	(0.561)	(0.809)	(0.161)	(0.296)
× Top tercile	−2.353**	−0.444	−0.263*	−0.872***
	(0.929)	(0.758)	(0.155)	(0.308)
Top − bottom tercile	−1.430	−2.046*	0.031	−0.353
	(1.051)	(1.210)	(0.147)	(0.393)
No. commuting zones	117	117	117	117
No. firms	140,973	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 by initial leverage and sector category, interacting both $dX_{r(j)}$ and the instrument with dummies for each combination of the sector category of firm j and the tercile of the 2010 leverage distribution that it belonged to. "Top − bottom tercile" reports the difference between the effects for the top and bottom leverage terciles among firms in each sector category. See Appendix Table E11 for further details on the specification. Column (1) considers as the outcome variable the change in firm j's log net tangible fixed assets per employee from 2010 to 2019. Column (2) considers the symmetric growth rate of its long-term debt from 2010 to 2019. Column (3) considers the change in the log mean wage of its full-time employees. Column (4) considers the change in its number of native employees relative to its total number of employees in 2010. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table E17: Heterogeneous Effects of Immigration from 2010 to 2019 by Initial Leverage and Cohort

	Log Capital Intensity (1)	Growth of Debt (2)	Log Mean Wage (3)	Native Employees (4)
Founded 2001–2010, by leverage in 2010:				
× Bottom tercile	−1.393**	1.795*	−0.386**	−0.330
	(0.567)	(0.982)	(0.158)	(0.332)
× Middle tercile	−1.510***	−2.662***	−0.335**	−0.464
	(0.447)	(0.613)	(0.169)	(0.293)
× Top tercile	−1.598**	−1.164**	−0.519***	−0.897**
	(0.709)	(0.445)	(0.150)	(0.370)
Top − bottom tercile	−0.205	−2.958***	−0.133	−0.567*
	(0.792)	(1.040)	(0.123)	(0.288)
Founded 1996–2000, by leverage in 2010:				
× Bottom tercile	−1.203	−0.994	−0.113	−0.441
	(1.094)	(1.935)	(0.172)	(0.355)
× Middle tercile	−0.422	−0.610	−0.262	0.038
	(0.937)	(0.866)	(0.190)	(0.430)
× Top tercile	−1.479	−0.303	−0.153	−1.227***
	(0.934)	(0.709)	(0.226)	(0.389)
Top − bottom tercile	−0.277	0.691	−0.040	−0.786
	(1.354)	(2.030)	(0.166)	(0.479)
Founded 1995 or before, by leverage in 2010:				
× Bottom tercile	−0.137	2.337***	−0.107	−0.267
	(0.464)	(0.696)	(0.138)	(0.185)
× Middle tercile	−0.562	0.072	−0.192	−0.229
	(0.593)	(0.612)	(0.150)	(0.215)
× Top tercile	−0.398	−0.266	−0.290*	−0.581**
	(0.448)	(0.435)	(0.168)	(0.232)
Top − bottom tercile	−0.260	−2.604***	−0.183	−0.314
	(0.533)	(0.664)	(0.118)	(0.250)
No. commuting zones	117	117	117	117
No. firms	140,973	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 by initial leverage and cohort, interacting both $dX_{r(j)}$ and the instrument with dummies for each combination of the cohort of firm j and the tercile of the 2010 leverage distribution that it belonged to. "Top − bottom tercile" reports the difference between the effects for the top and bottom leverage terciles among firms in each cohort. See Appendix Table E12 for further details on the specification. Column (1) considers as the outcome variable the change in firm j's log net tangible fixed assets per employee from 2010 to 2019. Column (2) considers the symmetric growth rate of its long-term debt from 2010 to 2019. Column (3) considers the change in the log mean wage of its full-time employees. Column (4) considers the change in its number of native employees relative to its total number of employees in 2010. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table E18: Heterogeneous Effects of Immigration from 2010 to 2019 by Initial Leverage and Initial Size

	Log Capital Intensity (1)	Growth of Debt (2)	Log Mean Wage (3)	Native Employees (4)
Bottom size tercile, by leverage in 2010:				
× Bottom tercile	−1.125**	1.136*	−0.141	−0.720**
	(0.492)	(0.675)	(0.152)	(0.300)
× Middle tercile	−1.038***	−1.189***	−0.216*	−0.684**
	(0.371)	(0.416)	(0.126)	(0.271)
× Top tercile	−0.646**	−1.233***	−0.321**	−0.747***
	(0.321)	(0.343)	(0.141)	(0.248)
Top − bottom tercile	0.479	−2.369***	−0.180**	−0.027
	(0.403)	(0.600)	(0.088)	(0.300)
Middle size tercile, by leverage in 2010:				
× Bottom tercile	−0.706*	1.368**	−0.293**	−0.404*
	(0.379)	(0.625)	(0.141)	(0.240)
× Middle tercile	−0.342	−0.627	−0.265*	−0.015
	(0.409)	(0.459)	(0.140)	(0.247)
× Top tercile	−0.962**	−0.575	−0.233*	−0.347*
	(0.391)	(0.426)	(0.122)	(0.205)
Top − bottom tercile	−0.256	−1.943***	0.060	0.058
	(0.399)	(0.545)	(0.066)	(0.256)
Top size tercile, by leverage in 2010:				
× Bottom tercile	−0.512	1.839**	−0.146	−0.239
	(0.441)	(0.793)	(0.137)	(0.231)
× Middle tercile	−0.807	−0.587	−0.222	−0.248
	(0.565)	(0.587)	(0.157)	(0.209)
× Top tercile	−0.935	−0.398	−0.372**	−0.937***
	(0.590)	(0.459)	(0.171)	(0.263)
Top − bottom tercile	−0.423	−2.237***	−0.226**	−0.698**
	(0.672)	(0.785)	(0.112)	(0.292)
No. commuting zones	117	117	117	117
No. firms	140,973	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 by initial leverage and initial size, interacting both $dX_{r(j)}$ and the instrument with dummies for each combination of the tercile of the 2010 size distribution that firm j belonged to and the tercile of the 2010 leverage distribution that it belonged to. "Top − bottom tercile" reports the difference between the effects for the top and bottom leverage terciles among firms in each size tercile. See Appendix Table E13 for further details on the specification. Column (1) considers as the outcome variable the change in firm j's log net tangible fixed assets per employee from 2010 to 2019. Column (2) considers the symmetric growth rate of its long-term debt from 2010 to 2019. Column (3) considers the change in the log mean wage of its full-time employees. Column (4) considers the change in its number of native employees relative to its total number of employees in 2010. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table E19: Heterogeneous Effects of Immigration from 2010 to 2019 by Initial Leverage and Initial Skill Intensity

	Log Capital Intensity (1)	Growth of Debt (2)	Log Mean Wage (3)	Native Employees (4)
Bottom skill tercile, by leverage in 2010:				
× Bottom tercile	−0.274	0.254	−0.211	−0.577**
	(0.689)	(0.646)	(0.153)	(0.270)
× Middle tercile	−0.141	−0.498	−0.127	−0.426*
	(0.554)	(0.599)	(0.155)	(0.247)
× Top tercile	0.011	−0.518	−0.193	−0.755***
	(0.472)	(0.519)	(0.121)	(0.221)
Top − bottom tercile	0.286	−0.771	0.018	−0.178
	(0.734)	(0.579)	(0.100)	(0.241)
Middle skill tercile, by leverage in 2010:				
× Bottom tercile	−0.186	2.517**	−0.035	−0.289
	(0.538)	(1.265)	(0.160)	(0.216)
× Middle tercile	−0.857	−0.419	−0.257	−0.519**
	(0.652)	(0.624)	(0.174)	(0.224)
× Top tercile	−0.475	−0.541	−0.361*	−0.980***
	(0.591)	(0.492)	(0.187)	(0.267)
Top − bottom tercile	−0.289	−3.058**	−0.326**	−0.691***
	(0.715)	(1.211)	(0.148)	(0.260)
Top skill tercile, by leverage in 2010:				
× Bottom tercile	−1.196**	1.264	−0.318**	−0.219
	(0.558)	(0.788)	(0.138)	(0.289)
× Middle tercile	−0.925**	−1.092*	−0.254*	0.325
	(0.441)	(0.593)	(0.130)	(0.261)
× Top tercile	−2.308***	−0.507	−0.390***	−0.436
	(0.656)	(0.452)	(0.138)	(0.300)
Top − bottom tercile	−1.113	−1.771**	−0.072	−0.216
	(0.742)	(0.870)	(0.065)	(0.445)
No. commuting zones	117	117	117	117
No. firms	140,973	140,973	140,973	140,973

Sources: Custom link between Moody's DataHub and Establishment History Panel; SIAB.
Notes: This table reports estimates of the heterogeneous effects of immigration from 2010 to 2019 by initial leverage and initial skill intensity, interacting both $dX_{r(j)}$ and the instrument with dummies for each combination of the tercile of the 2010 skill intensity distribution that firm j belonged to and the tercile of the 2010 leverage distribution that it belonged to. "Top − bottom tercile" reports the difference between the effects for the top and bottom leverage terciles among firms in each skill intensity tercile. See Appendix Table E14 for further details on the specification. Column (1) considers as the outcome variable the change in firm j's log net tangible fixed assets per employee from 2010 to 2019. Column (2) considers the symmetric growth rate of its long-term debt from 2010 to 2019. Column (3) considers the change in the log mean wage of its full-time employees. Column (4) considers the change in its number of native employees relative to its total number of employees in 2010. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.