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ABSTRACT

How Do Industries and Firms Respond to Changes in Local Labor Supply?*

In this paper, we investigate how changes in the skill mix of local labor supply are absorbed by the economy. We distinguish between three adjustment mechanisms: through factor prices, through an expansion in the size of those production units that use the more abundant skill group more intensively, and through more intensive use of the more abundant skill group within production units. We investigate which of these channels is dominant. We contribute to the existing literature by analyzing these adjustments on the level of firms, rather than industries, and by assessing the role of new firms in the absorption process of labor supply shocks. Our analysis is based on administrative data, comprising the entirety of firms in Germany over a 10 years period. We find that, while factor price adjustments are important in the non-tradable sector, labor supply shocks do not induce factor price changes in the tradable sector. In this sector, most of the adjustment to changes in relative factor supplies takes place within firms by changing relative factor intensities. Given the non-response of factor prices, this finding points towards changes in production technology. Our results further show, that firms that enter and exit the market are an important additional channel of adjustment. Finally, we demonstrate that an industry level analysis is likely to over-emphasize technology-based adjustments.

JEL Classification: F1, J2, J61, L2, O3

Keywords: immigration, endogenous technological change, firm structure

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1 Introduction

How are changes in local labor supply absorbed by the local economy? This question has gained relevance over the past two decades, amid a dramatic increase in national and international migrations. Labor economists typically assume that the main channel of adjustment is through changes in factor prices, and a large and growing literature assesses the magnitude of these adjustments.[1] Trade economists, on the other hand, emphasize that the local economy can also adjust through changes in the output mix, with those production units growing faster that use the more abundant factor more intensively (see Rybczynski, 1955).[2] Finally, production units in the local economy could adjust through changes in their production technology, by adopting new technologies that make more intensive use of the more abundant factor. This adjustment can take place either through an endogenous choice of the direction of research by profit-maximizing innovators so that new technological innovations available to firms are complementary to particular factor supply conditions (see, for example, Acemoglu, 1998, 2002), or through firms optimally adopting a production technology out of a given pool of alternatives with respect to the factor supplies they are facing (see Atkinson and Stiglitz, 1969, Basu and Weil, 1998, Caselli, 1999, Beaudry and Green, 2003, 2005, Caselli and Coleman, 2006).[3]

A number of recent papers have empirically investigated the magnitude of adjustments through output mix and technology, usually on the level of industries, and often by using immigration as a trigger for changes in relative factor supplies. For instance, Quispe-Agnoli and Zavodny (2002) analyze the relationship between immigration and output mix, labor productivity, and capital investment in the U.S. manufacturing sector between

[1] See for instance, Pischke and Velling (1997), Card (2001), Borjas (2003), Dustmann et al. (2005), Dustmann et al. (2008), Ottaviano and Peri (2011), Manacorda et al. (2011), or Glitz (2011). For an overview, see Okkerse (2008).

[2] The broad predictions of the Rybczynski theorem and the closely related Factor Price Insensitivity Theorem (Leamer and Levinsohn, 1995) hold as long as there are at least as many tradable goods as factors of production (see, for example, Ethier, 1984, for details) and can be extended to account for the existence of non-tradable goods (see Komiya, 1967 and Ethier, 1972). Studies by Davis et al. (1997) for Japan, Bernhard et al. (2002) for the UK, and Hanson and Slaughter (2002) for the U.S. investigate the validity of the Heckscher-Ohlin-Samuelson theory – which is the foundation of the Rybczynski and Factor Price Insensitivity Theorems – within individual countries.

[3] Recent empirical evidence that computer use as well as automation expand most rapidly in those areas where the relative supply of skilled labor grows fastest points towards the importance of this demand-side explanation (Doms and Lewis, 2006, Beaudry et al., 2010, Lewis, 2011).

1982 and 1992, while Hanson and Slaughter (2002) examine more generally the mechanisms through which U.S. states absorb changes in labor supplies between 1980 and 1990, distinguishing explicitly between changes in the output mix and changes in production techniques across industries. Following a similar approach for the same period but with both geographically and industrially more disaggregated data, Lewis (2003) analyzes the extent to which the industry mix in U.S. metropolitan areas adjusts to changes in local factor supplies caused by immigration.[4] Both Hanson and Slaughter and Lewis find that most of the adjustment happens through within-industry changes, interpreted as changes in production technology.[5] Following the same approach, González and Ortega (2011) come to similar conclusions for Spain for the period 2001 to 2006.

One potential problem with carrying out the analysis at the industry level is that firms within industries are heterogeneous, so that scale adjustments between firms that operate within the same industry may be incorrectly interpreted as factor intensity adjustments due to technology changes. Furthermore, an aggregation to the level of industries will not capture the role of new firms entering the production process and that of dying firms leaving it. Given the high turnover of firms, and new firms' lower adjustment costs, this could be an important omission.[6] Finally, if some of these adjustments do indeed take place through the creation of new firms, it is likely that small firms play a particularly important part in the overall adjustment process.

In this paper, we make a number of contributions. First, we provide a novel decomposition of the effects of labor supply shocks on the level of the individual production unit, and we assess the bias that results from a decomposition on the level of industries.[7] We demonstrate that - if firms within industries are heterogeneous - an analysis on the

[4]See also Gandal et al. (2004) and Card and Lewis (2007) for related analyses.

[5]While Lewis (2003) concludes that industries are changing their production technologies to complement the changes in local factor supplies (see also Lewis, 2004), Hanson and Slaughter (2002) further separate industry-wide changes in production technology that are common across all states from industry-state-specific changes in production technology. They show that the latter account for only relatively little factor absorption, which speaks against region-specific changes in the production techniques of different industries in response to changes in local factor supplies due to immigration.

[6]In our sample of all firms in Germany, and over the period we observe, turnover is about 50%. This figure is in line with findings for the United States. For example, Dunne et al. (1989a,b) find that 40% of firms in manufacturing in the U.S. disappear over a five year period and are replaced by new entrants.

[7]Our data refers to establishments rather than legal firm units, which we believe is the appropriate unit for the purpose of our analysis. For simplicity, we refer to these as "firms" or "production units".

industry level may lead to a substantial bias in the distinction of output mix and technology adjustments. Secondly, we explicitly account for the creation of new firms and the deaths of existing firms, in explaining the absorption of changes in factor supplies, and we suggest a way to decompose these into output and technology adjustments. Finally, we implement our decomposition using administrative data for the entire workforce in Germany between 1985 and 1995. This has been a period with large labor supply shocks through immigration. We use the component of these shocks that can be explained by past settlement patterns of immigrants, to isolate absorption mechanisms that respond to supply shocks from the absorption of labor supply changes that are possibly induced by demand shocks.

Most of our analysis focusses on tradable industries and the firms that operate within those industries. As a first step, we assess the impact of immigration on wages. We find that immigration had no relative wage effects on workers in the tradable sector over the period we consider. This is in contrast to our findings for the non-tradable sector, where immigration led to a decrease in relative wages of those workers who are in the same skill group as immigrants: a 1 percent increase in skill-specific labor supply decreases relative wages by around 0.5 percent. This finding contributes to the literature on the impact of immigration, which so far does not draw a distinction between tradable and non-tradable sectors. Our findings suggests that for the analysis of wage effects, it may be important to distinguish between these sectors.[8]

The results from our main decomposition show that changes in skill specific local employment are associated with both an increase in the size of firms that use the more abundant factor more intensively (and hence with changes in the local output mix), and with changes in the production technology of existing firms, in a direction that makes more intensive use of the more abundant factor. In line with the earlier literature on the industry level, our findings suggest that in terms of relative magnitudes, output mix changes do not play a major role in accommodating changes in local factor endowments,

[8]The different findings for the tradable and the non-tradable sector also point towards imperfect mobility of workers between sectors. Monras (2011) explores how such sluggishness of workers could impede the adjustment process to local labor supply shocks.

even on the firm level. However, we also find that the net effect of newly created firms and dying firms is important for the adaptation to changing factor supply conditions.

These findings are informative about the relationship between changes in relative labor supply, and the structure of production in the tradable sector, but do not speak to the question of how exogenous changes in local labor supply are absorbed by firms in that sector, as it may be changes in local demands that induce skill specific changes in labor supply. Focussing in a second step on skill specific labor supply shocks caused by immigration, we find that scale adjustments of existing firms are even smaller. This points towards reverse causality in simple decompositions, through expanding firms across regions inducing labor supply responses. However, the within-firm effect remains significant and large, and explains around 70% of the overall adjustment to immigration-induced labor supply shocks. We show that also in this context, the net creation of new firms is an important adjustment channel, contributing another 18% to the overall adjustment.

When assessing the bias induced by aggregating up firms to the level of industries, our results show that industry decompositions conceal an important part of the adjustment processes that take place. For instance, while on the industry level it appears that immigration-induced labor supply shocks do not lead to any scale adjustment, analysis on the firm level shows that these adjustments do take place, but through the creation of new firms rather than an expansion of already existing firms.

The structure of the paper is as follows. In the next section, we explain our analytical framework. In Section 3, we describe the data and provide some descriptive evidence on the industry and firm structure in West Germany between 1985 and 1995. In Section 4, we present our empirical results. We first show the extent to which local relative wage rates have responded to changes in local factor supplies (Section 4.1), and then present the main firm-level estimates of the relative contribution of output and technology adjustments to the absorption of local labor supply shocks (Section 4.2). We discuss the specific role of new and old firms in this process, and relate the firm-level results to those that would be obtained by an industry-level analysis (Section 4.3). Finally, we provide some additional results on the role of firm size and nationwide changes in industry-specific

production technologies for the adjustment process (Section 4.4). Section 5 summarizes and concludes.

2 Analytical Framework

2.1 Theoretical Motivation

Suppose there are many regions R, each with production units j ($j = 1, ..., J$) producing output goods Y^j with a constant returns to scale technology, and using $i = 1, ..., K$ labor inputs. In equilibrium, factor supply in each region is equal to factor demand, so that the $(K \times 1)$ vector of factor supplies X in a particular region can be written as

$$X = \sum_{j=1}^{J} C_W^j(W, A^j)Y^j,$$

where $C_W^j(W, A)$ are the $(K \times 1)$ vectors of unit factor demands in production unit j (the partial derivatives of the unit cost function with respect to each group's own wage), showing the units of labor input i required to produce one unit of output Y^j, A^j is a vector of technology coefficients affecting the factor specific unit demands, and W is a vector of factor prices. Totally differentiating (1) and re-arranging terms, we obtain:

$$dX = \sum_{j=1}^{J} Y^j C_{WW}^j dW^j + \sum_{j=1}^{J} C_W^j dY^j + \sum_{j=1}^{J} Y^j C_{WA^j}^j dA^j. \quad (1)$$

Here C_{WW}^j is the $(K \times K)$ matrix of cross-price effects on factor demands for production unit j, which is negative semi-definite given our assumption about the production technology, and $C_{WA^j}^j$ is a $(K \times K)$ matrix that measures the changes in unit factor demands induced by changes in the production technology. Consider the first term on the right hand side of Equation (1), which reflects the adjustment to changes in labor supply through changes in factor prices. Since C_{WW}^j is negative semi-definite, changes in factor supply and changes in wages will negatively co-vary: if immigration is the cause for the changes in factor supply, wages will decrease for those workers who have the same skills

as immigrants, as they become relatively more abundant. Note that this does not mean that average wages are decreasing, as their level is generally determined by the elasticity of capital supply (see, for example, Dustmann et al., 2008).[9] This is the usual channel along which immigration effects are analyzed in much of the empirical literature.

The second term on the right-hand side is the change in output between production units, weighted by the production unit specific vector of unit factor demands. This means that a supply shock could be absorbed through a change in the structure of production, by an expansion in output of production units that use the more abundant factor more intensively, keeping relative unit factor demands constant. Finally, the last term reflects shifts in factor demands through changes in technology within production units, weighted by the change in the unit factor demands induced by such technology shifts, and holding the relative size of output across production units constant.

The total differential in Equation (1) illustrates the different channels through which a regional economy can adjust to changes in the supply of workers. Following the factor price insensitivity theorem, if all regions share the same technologies to produce a sufficient number of traded goods, prices for these goods are fixed on the national (or international) market, and if the supply shock to a particular region is not too large, a change in labor supply will not affect factor prices. In this case, the first term on the right hand side of equation 1 will be zero and adjustment takes place either through a trade-induced shift of production towards those goods that use the now relatively abundant factor more intensively (second term), or through changes towards production technologies that make more use of the more abundant factor (third term). Note that constant factor prices also imply that $C^j_{WA^j} dA^j = dC^j_W(W, A^j)$: the only way unit factor demands can change is through changes in technology.

Our empirical analysis is motivated by Equation (1). What we first show is that relative factor prices in the tradable sector do not change in response to labor supply shifts, so that the first term in equation (1) is effectively zero. Focussing on a particular

[9] In our simplified model, we have abstracted from capital, which is equivalent to assume that capital is infinitely elastic. In that case, the overall effect on wages of small changes in relative factor supplies is zero.

skill group i, the percentage change in labor supply in that skill group relative to a base period (denoted by the subscript 0) can then be written as

$$\frac{\Delta X_i}{X_{i_0}} = \sum_{j=1}^{J} \frac{C_{wi}^j Y^j}{X_{i_0}} \frac{dY^j}{Y^j} + \sum_{j=1}^{J} \frac{C_{wi}^j Y^j}{X_{i_0}} \frac{dC_{wi}^j}{C_{wi}^j}.$$

In our empirical analysis, we approximate C_{wi}^j, the unit factor demand of skill group i in production unit j, by the ratio of the number of employees of skill group i in that production unit, N_{ij}, and the total number of employees, M_j, so that $\frac{dC_{wi}^j}{C_{wi}^j} = \%\Delta(\frac{N_{ij}}{M_j})$. Further, we approximate percentage changes in output Y^j by percentage changes in the total workforce M_j.[10] Denoting the fraction of employment in skill group i in production unit j relative to overall labor supply in skill group i in the base period as $s_{ij_0} = \frac{N_{ij_0}}{X_{i_0}}$, we obtain

$$\frac{\Delta X_i}{X_{i_0}} \approx \sum_{j=1}^{J} s_{ij_0} \%\Delta M_j + \sum_{j} s_{ij_0} \%\Delta(\frac{N_{ij}}{M_j}). \tag{2}$$

2.2 Empirical Decomposition

We now turn to the empirical implementation. We focus on adjustments of local economies to factor supply shocks through changes in the output mix and through changes in production technologies within production units. As Equation (2) shows, we capture these by changes between production units in the scale of their production ("scale effects" or "between effects"), and by changes in the relative use of a particular factor in the production process within a given production unit ("intensity effects" or "within effects").

An important decision at this stage is to determine the level at which production is measured. A main contribution of our paper is that we are able to consider the firm as the unit of production. We commence by decomposing the change in labor supply into scale and intensity effects in firms that exist in both periods we consider, and the net contribution of new firms. In our empirical analysis, we focus on the contribution of the

[10] This is not unreasonable in this context and possibly a more direct measure than output itself, as employment is comparable across firms, and what we intend to capture is the employment change embodied in output changes.

tradable sector only as the tradability of the output goods is a prerequisite for the scale adjustments described in the previous section. Thus, in a first step, we subtract from the actual observed change in skill-specific local labor supply the part that is absorbed by the non-tradable sector. In addition, while the theoretical derivation in the previous section assumes that factor demand and supply are always in equilibrium, in the empirical implementation we need to take account of unemployment. As the focus of this paper is on adjustments in the employment structure across and within production units, we subtract the part of the observed change in labor supply that is absorbed through additionally unemployed individuals. The change in skill-specific employment in the tradable sector is then given by

$$\Delta N_i = \Delta X_i - \Delta N_i^{NT} - \Delta U_i,$$

where ΔN_i is the change in employment of skill group i over our observation period, and ΔX_i, ΔN_i^{NT}, and ΔU_i are the changes in overall labor supply, employment in the non-tradable sector, and unemployment of skill group i. Dividing the left-hand side by the total employment of skill group i in the tradable sector in the base period, the change in skill-specific employment in all firms f in the tradable sectors j in a local labor market can be written as:

$$\begin{aligned}
\frac{\Delta N_i}{N_{i_0}} = \%\Delta N_i = &\sum_j \sum_{f \in \mathcal{N}^p} s_{ijf_0} \cdot \%\Delta M_{jf} && \text{permanent firm scale effect} \\
&+ \sum_j \sum_{f \in \mathcal{N}^p} s_{ijf_0} \cdot \%\Delta \left(\frac{N_{ijf}}{M_{jf}} \right) && \text{permanent firm intensity effect} \\
&+ \sum_j \sum_{f \in \mathcal{N}^p} s_{ijf_0} \cdot \%\Delta M_{jf} \cdot \%\Delta \left(\frac{N_{ijf}}{M_{jf}} \right) && \text{permanent firm residual term} \\
&+ \sum_j \sum_{f \in \mathcal{N}^n} \frac{N_{ijf}}{N_{i_0}} - \sum_j \sum_{f \in \mathcal{N}^o} \frac{N_{ijf_0}}{N_{i_0}} && \text{net new firm contribution}
\end{aligned} \tag{3}$$

where M_{jf} measures the overall employment, and N_{ijf} the skill-specific employment in a firm. The sets $\mathcal{N}^p$, $\mathcal{N}^n$ and $\mathcal{N}^o$ denote *permanent* (p) firms that exist both at the beginning and the end of our 10 year observation window, *new* (n) firms that do not exist

at the beginning, but do exist at the end of the observation window, and *old* (o) firms that exist at the beginning but not at the end of our observation window, respectively. The variable $s_{ijf_0} = N_{ijf_0}/N_{i_0}$ is the share of all workers with skill level i in the overall tradable sector that is employed in (permanent) firm f in the base period 0, and can be interpreted as a firm/skill group specific weight. Finally, N_{ijf} in the last row of the expression in (3) is the skill-specific employment in a new firm at the end of the observation period, and N_{ijf_0} the skill-specific employment in an old firm at the start of the observation period.[11] For details of this derivation, see Appendix B-1. Notice the close correspondence between the decomposition shown in Equation (3) and our theoretically motivated derivation of Equation (2).

The first term in Equation (3) captures the contribution of changes in the size of permanent firms, $\%\Delta M_{jf}$, to the absorption of changes in local labor supply, holding relative factor inputs constant. The second term captures the contribution of changes in relative factor inputs within a permanent firm, $\%\Delta(N_{ijf}/M_{jf})$, and the third term captures a residual component that cannot be clearly assigned to either of the first two components.

The last term in Equation (3) captures the contribution through the creation and destruction of firms. This contribution can again be interpreted as a scale or an intensity effect. However, because these firms did not exist either at the beginning or at the end of the observation window, one cannot use the firm-specific growth rates in scale and skill-specific factor intensities to distinguish between the two. One way to decompose the net contribution of new firms is to benchmark it against the industry they operate in in the year in which they are created or shut down. We thus compute - for each entering or exiting firm in our 10 years observation window - the average technology (in terms of relative factor inputs) of the industry they belong to in the year of entry or exit. Their contribution in that particular year can be interpreted as a pure scale effect if their factor intensities coincide with the contemporaneous industry average, or as an intensity effect if they enter and exit with different relative factor inputs which may or

[11] Note that whenever a variable refers to the end of the observation period, we drop the time subscript for simplicity.

may not be conducive to the absorption of local labor supplies. After the year of their entry (before the year of their exit), new (old) firms can be considered as permanent firms and their growth in scale and factor intensity treated in the same way as for our initial set of permanent firms. Following this argument, we decompose in Appendix B-2 the net contribution of new and old firms in the last row of Equation (3) into a scale component and an intensity component (each of which is the sum of the corresponding contribution at entry (exit) and the contribution over time).

2.3 Firm versus Industry Decomposition

What is the aggregation error of this decomposition if carried out on the industry level, as opposed to the firm level? Consider first the standard decomposition on the industry level (see e.g. Lewis, 2003):

$$\begin{aligned} \%\Delta N_i = & \sum_j s_{ij_0} \cdot \%\Delta M_j && \text{industry scale effect} \\ & + \sum_j s_{ij_0} \cdot \%\Delta \left(\frac{N_{ij}}{M_j} \right) && \text{industry intensity effect} \\ & + \sum_j s_{ij_0} \cdot \%\Delta M_j \cdot \%\Delta \left(\frac{N_{ij}}{M_j} \right) && \text{industry residual term,} \end{aligned} \tag{4}$$

where M_j measures the overall employment and N_{ij} the skill-specific employment in industry j, and $s_{ij_0} = N_{ij_0}/N_{i_0}$ denotes industry/skill group specific weights, computed with respect to the base year.[12] For details of this derivation, see Appendix B-3.

To see how these terms are related to the decomposition on the firm level, consider

[12] A very small number of industries did either not exist at the beginning of the observation period in some regions, or by the end of the observation period. The overall contribution of these industries to the absorption of local supply changes is negligible (between 0.3% and 0.9%), and we subtract these contributions prior to the empirical decompositions from the overall skill-specific changes in local labor supply. This significantly facilitates the exposition of the results and ensures that the identities in Equations (3) and (4) continue to hold.

first the scale effect:

$$\underbrace{\sum_j s_{ij_0} \cdot \%\Delta M_j}_{\text{industry scale effect}} = \underbrace{\sum_j \sum_{f \in \mathcal{N}^p} s_{ijf_0} \cdot \%\Delta M_{jf}}_{\text{permanent firm scale effect}} \tag{5}$$

$$+ \underbrace{\sum_{t=1}^{T} \sum_j \sum_{f \in \mathcal{N}_t^n} \left(\frac{N_{ij_t}}{N_{i_0}}\right)\left(\frac{M_{jf_t}}{M_{j_t}}\right) - \sum_{t=0}^{T-1} \sum_j \sum_{f \in \mathcal{N}_t^o} \left(\frac{N_{ij_t}}{N_{i_0}}\right)\left(\frac{M_{jf_t}}{M_{j_t}}\right)}_{\text{net new firm entry scale}}$$

$$+ \underbrace{\begin{aligned} &\sum_{t=1}^{T} \sum_j \sum_{f \in \mathcal{N}_t^n} \left(\frac{N_{ijf_t}}{N_{i_0}}\right) \%\Delta_t^T M_{jf_t} + \sum_{t=0}^{T-1} \sum_j \sum_{f \in \mathcal{N}_t^o} \left(\frac{N_{ijf_0}}{N_{i_0}}\right) \%\Delta_0^t M_{jf_t} \\ &+ \frac{1}{2}\left(\sum_{t=1}^{T} \sum_j \sum_{f \in \mathcal{N}_t^n} \frac{N_{ijf_t}}{N_{i_0}} \%\Delta_t^T M_{jf_t} \%\Delta_t^T \left(\frac{N_{ijf_t}}{M_{jf_t}}\right) + \sum_{t=0}^{T-1} \sum_j \sum_{f \in \mathcal{N}_t^o} \frac{N_{ijf_0}}{N_{i_0}} \%\Delta_0^t M_{jf_t} \%\Delta_0^t \left(\frac{N_{ijf_t}}{M_{jf_t}}\right)\right) \end{aligned}}_{\text{net new firm growth scale}}$$

$$+ \text{aggregation bias scale},$$

where $\mathcal{N}_t^n$ and $\mathcal{N}_t^o$ refer to the sets of new and old firms that were the first or the last time observed in year t, respectively. Note that $\%\Delta_a^b X$ refers to the change in X between period a and period b.

Now consider the intensity effect:

$$\underbrace{\sum_j s_{ij_0} \cdot \%\Delta\left(\frac{N_{ij}}{M_j}\right)}_{\text{industry intensity effect}} = \underbrace{\sum_j \sum_{f \in \mathcal{N}^p} s_{ijf_0} \cdot \%\Delta\left(\frac{N_{ijf}}{M_{jf}}\right)}_{\text{permanent firm intensity effect}} \tag{6}$$

$$+ \underbrace{\begin{aligned} &\sum_{t=1}^{T} \sum_j \sum_{f \in \mathcal{N}_t^n} \left(\frac{N_{ij_t}}{N_{i_0}}\right)\left(\frac{M_{jf_t}}{M_{j_t}}\right)\left(\frac{\frac{N_{ijf_t}}{M_{jf_t}} - \frac{N_{ij_t}}{M_{j_t}}}{\frac{N_{ij_t}}{M_{j_t}}}\right) \\ &- \sum_{t=0}^{T-1} \sum_j \sum_{f \in \mathcal{N}_t^o} \left(\frac{N_{ij_t}}{N_{i_0}}\right)\left(\frac{M_{jf_t}}{M_{j_t}}\right)\left(\frac{\frac{N_{ijf_t}}{M_{jf_t}} - \frac{N_{ij_t}}{M_{j_t}}}{\frac{N_{ij_t}}{M_{j_t}}}\right) \end{aligned}}_{\text{net new firm entry intensity}}$$

$$+ \underbrace{\begin{aligned} &\sum_{t=1}^{T} \sum_j \sum_{f \in \mathcal{N}_t^n} \left(\frac{N_{ijf_t}}{N_{i_0}}\right) \%\Delta_t^T \left(\frac{N_{ijf_t}}{M_{jf_t}}\right) + \sum_{t=0}^{T-1} \sum_j \sum_{f \in \mathcal{N}_t^o} \left(\frac{N_{ijf_0}}{N_{i_0}}\right) \%\Delta_0^t \left(\frac{N_{ijf_t}}{M_{jf_t}}\right) \\ &+ \frac{1}{2}\left(\sum_{t=1}^{T} \sum_j \sum_{f \in \mathcal{N}_t^n} \frac{N_{ijf_t}}{N_{i_0}} \%\Delta_t^T M_{jf_t} \%\Delta_t^T \left(\frac{N_{ijf_t}}{M_{jf_t}}\right) + \sum_{t=0}^{T-1} \sum_j \sum_{f \in \mathcal{N}_t^o} \frac{N_{ijf_0}}{N_{i_0}} \%\Delta_0^t M_{jf_t} \%\Delta_0^t \left(\frac{N_{ijf_t}}{M_{jf_t}}\right)\right) \end{aligned}}_{\text{net new firm growth intensity}}$$

$$+ \text{aggregation bias intensity}.$$

Thus, both scale and intensity effects estimated on the industry level do not distinguish between adjustments through firms that are observed in both periods, and adjustments

through new firms. The final terms in Equations (5) and (6), shown in Appendix B-4, reflect the aggregation bias when using industry rather than firm level decompositions.

Under which assumptions will the empirical analysis on the industry and firm level lead to the same conclusions with regard to the relative magnitude of between and within effects? Ignore for the moment the contribution of new and old firms, and suppose for now there are only permanent firms. The industry scale effect in Equation (4) and the permanent firm scale effect in Equation (3) will be the same if the corresponding bias term for permanent firms, given by $\sum_j \sum_{f \in \mathcal{N}^p} s_{ij_0}(\frac{M_{jf_0}}{M_{j_0}} - \frac{N_{ijf_0}}{N_{ij_0}})\%\Delta M_{jf}$, (see Appendix B-4) is zero. This happens trivially if all firms in the same industry j produce with the same relative factor inputs in the base year. In this case, $(\frac{M_{jf_0}}{M_{j_0}} - \frac{N_{ijf_0}}{N_{ij_0}}) = 0$, and the industry-based scale effect will be identical to the firm-based scale effect. More generally, the decompositions on the industry and firm level will be identical as long as the (weighted) factor intensities employed in different firms (relative to the industry average) are uncorrelated with the firms' growth rates. However, if, for instance, those firms within an industry that (in comparison to their relative size) are particularly intensive in the use of a given skill input i (so that $(\frac{M_{jf_0}}{M_{j_0}} - \frac{N_{ijf_0}}{N_{ij_0}}) < 0$) grow at a faster rate, then the residual term will be negative, which means that an industry level analysis *underestimates* the true contribution through scale adjustments.

Similarly, the intensity effect calculated at the firm level equals the intensity effect at the industry level if all firms in the same industry j grow at the same rate (so there is no "between" effect within industries). In this case, $(\frac{M_{jf}}{M_{jf_0}} - \frac{M_j}{M_{j_0}}) = 0$. More generally, as long as the (weighted) firms' growth rates (relative to the industry average) are uncorrelated with the change in their relative factor intensities, the firm level aggregation is equal to the industry level aggregation.

In addition to the potential biases arising from heterogeneity of permanent firms within industries, the presence of new and old firms adds an additional source of bias to the industry level analysis. The bias terms in Equations (5) and (6), spelled out in detail in Appendix B-4, provide a summary measure of the overall aggregation bias.

2.4 Estimation Strategy

In order to obtain summary measures of the relative contribution of adjustments in scale and intensity to the absorption of changes in local labor supply, we regress each of the components in either Equation (3) or Equation (4) on the percentage change in labor supply in a region, conditional on a full set of region fixed effects θ_r, which account for scale effects common to all firms and skill groups in a region, and skill group fixed effects λ_i, which account for exogenous changes in the relative usage of different labor types in all firms and regions. As we estimate identities, the regression coefficients for each of the single terms will have to sum up to 1, so that we can interpret the coefficient estimates as the relative contribution of the corresponding component to the absorption of changes in labor supply on the local level.[13] For the permanent firm scale effect, for instance, the estimation equation is given by

$$\sum_{j_r} \sum_{f \in \mathcal{N}_r^p} s_{ijf_0} \cdot \%\Delta M_{jf} = y_{ir} = \theta_r + \lambda_i + \beta \%\Delta N_{ir} + \varepsilon_{ir},$$

where r denotes the labor market region.

How can we interpret the parameter estimates? A positive estimate for β indicates that an increase in labor supply of, for example, low skilled workers increases the scale of firms that use low skilled workers more intensively in those regions that are affected. However, it may also indicate that workers go to regions where firms expand that use their particular skill type intensively. Thus, results from straightforward regressions do not have a causal interpretation. They are nevertheless informative, as they answer the question how changes in relative local labor supplies are associated with adjustments between and within firms.

To address the question how local industries react to exogenous changes in relative factor supplies, we instrument the relative changes in skill-specific employment in a locality

[13] To see that, consider the identity $y = x_1 + x_2$. Regressing x_1 and x_2 on a constant and y gives estimates $\hat{b_1} = Cov(y, x_1)/Var(y)$ and $\hat{b_2} = Cov(y, x_2)/Var(y)$. Since $Var(y) = Var(x_1) + Var(x_2) + 2Cov(x_1, x_2)$, $\hat{b_1} + \hat{b_2} = 1$.

with predictions of international immigration into the area based on historical settlement patterns, following Card (2001), and implemented in a similar setting by Lewis (2003). Under the plausible assumption that current regional labor market shocks are uncorrelated with past settlement patterns of immigrants, this leads to estimates that have a causal interpretation. For a detailed explanation of how we construct the instrument, see Appendix C.

In Section 2, we show that one adjustment mechanism to changes in local labor supply is through relative factor prices. If factor price adjustment takes place, then within-firm changes in relative factor usage may be induced by changes in relative factor prices, shifting the unit factor demands C_W. Such changes cannot be interpreted as changes in technology. Thus, as a first step, we investigate to what extent labor supply shocks have led to adjustments in local relative factor prices. To do this, we estimate the following model:

$$\Delta \log w_{ir} = \delta_r + \eta_i + \gamma \% \Delta X_{ir} + \varepsilon_{ir}, \tag{5}$$

where $\Delta \log w_{ir}$ is the percentage change in gross daily median wages and $\% \Delta X_{ir}$ the percentage growth of the labor force with education level i in region r. The vectors δ_r and η_i are full sets of region and skill fixed effects. As before, unobserved skill-specific local labor demand shocks may attract workers of a given skill group into a particular region while at the same time increasing that group's wages, leading to upward biased OLS estimates of the parameter γ. We address this by using the same instrument as in the analysis of the relative contributions of scale and intensity effects.

3 Data and Descriptive Evidence

The data base we use for our analysis is the universe of the German social security records which are provided by the Institute for Employment Research (IAB). The data comprise the employment histories of all dependent employees who are subject to social security contributions in Germany. It includes all wage earners and salaried employees but excludes

the self-employed, civil servants, and the military.[14] The social security records include an identifier for the firm an individual is working in. We use this identifier to construct a yearly panel of all firms in Germany that includes information about their skill-specific employment and wages, the industry they belong to, and the region they operate in.[15] Our analysis is based on West-Germany only, to which we refer for simplicity as "Germany".[16] Labor market regions are aggregates of Germany's 326 counties, which take commuter flows into account so that they better reflect separate local labor markets. There are 204 labor market regions in our data. In 1995, each labor market region comprises on average around 315,000 individuals.

One major advantage of using the universe of the workforce is that we are able to capture all firms. Most firm-level datasets such as the Annual Survey of Manufactures for the U.S. are biased towards large establishments. Since the aim of this paper is to analyze changes in aggregate industry and firm growth as well as firm-level technology adjustments, and the majority of firms is small with about 20 employees on average, to focus on large establishments could lead to potentially misleading conclusions. We base our analysis on all individuals who are aged between 15 and 64 and who work full-time. We differentiate between three skill groups, which we classify as low, intermediate and high. Individuals with low education are individuals without post-secondary education. Individuals with intermediate education have obtained post-secondary vocational or apprenticeship degrees, and individuals with high education have attended college. This is a standard classification in the German context (see e.g. Antonczyk et al., 2010).

Throughout the analysis, we focus on the period 1985 to 1995, over which substantial immigration to Germany took place. Table 1 provides an overview of the size and compo-

[14] In 2001, 77.2% of all workers in the German economy were covered by the social security system (Bundesagentur für Arbeit, 2004).

[15] The wage records in the IAB data sample are top coded at the social security contribution ceiling. This can be severe for individuals in the highest skill group. Across regions, the mean fraction of individuals with censored wage observations is 0.6% for the low-skilled, 5.0% for the medium-skilled, and 41.6% for the high-skilled. Throughout the analysis we therefore use median wages and indicate whenever the median wage remains subject to censoring, i.e. when more than 50% of the observations within the high-skill group are censored. All wages are gross daily wages in real 1995 Euro terms based on the consumer price index for all private households.

[16] West Germany's unification with East Germany took place on the 3rd of October 1990 but data on East Germany is only included in the IAB data from 1992 onwards. Therefore, we focus exclusively on labor market regions in West Germany, excluding Berlin.

Table 1: Summary Statistics of Immigrant Inflow, 1985 to 1995

	Immigrant Inflow	% Share of Inflow	Low Education	Intermediate Education	High Education
Former Yugoslavia	765,974	26.1	47.6	44.8	7.6
Asia	467,736	15.9	58.4	25.0	16.6
Poland	377,723	12.9	24.8	60.5	14.8
Turkey	321,242	11.0	78.4	16.8	4.9
Former Soviet Union	243,767	8.3	31.0	38.0	31.1
Western Europe	162,030	5.5	27.0	42.4	30.6
Africa	152,250	5.2	69.4	22.0	8.7
Romania	147,020	5.0	41.3	41.1	17.5
Central & Eastern Europe	107,677	3.7	35.3	47.7	17.0
Greece	68,505	2.3	68.2	27.9	3.8
Portugal	51,175	1.7	73.3	22.1	4.5
Italy	36,941	1.3	65.3	24.6	10.1
Central & South America	36,778	1.3	34.8	32.3	32.9
North America	7,712	0.3	32.5	15.1	52.4
Others	-13,045	−0.4	39.5	27.7	32.8
All	2,933,485	100.0	48.6	37.4	14.0

Source: Statistical Office and German Microcensus. Immigrant inflow refers to the net overall inflow between 1985 and 1995. The skill distribution refers to the educational attainment of immigrants aged 15 to 64 at the time of entry, calculated using available information from the German Microcensus that is closest to the actual year of arrival. Individuals with low education are individuals without post-secondary education. Individuals with intermediate education have obtained post-secondary vocational or apprenticeship degrees, and individuals with high education have attended college.

sition of the net foreign immigrant inflow to Germany between 1985 and 1995.[17] Overall, nearly 3 million new immigrants arrived in Germany during that period, corresponding to a net inflow rate (relative to the West German population in 1985) of 5.0%. Of these immigrants, more than a quarter originated from the territory of Former Yugoslavia as a result of the civil wars in the first half of the 1990s. The next biggest groups of immigrants came from Asia (15.9%), Poland (12.9%) and Turkey (11.0%). There is substantial variation in the immigrant inflows across labor market regions, varying between -0.6% (*Rhein-Hunsrück-Kreis*) and 8.9% (*Krefeld*) with a standard deviation of 1.7%. Overall, the newly arriving immigrants were relatively low-skilled compared to the native German population in 1995: 48.6% had low educational attainment, compared to 25.2% of the German population.[18] However, there is substantial variation across countries of

[17]In addition to the significant inflow of foreign immigrants, a large group of ethnic German immigrants arrived in Germany over the 1990s. As these immigrants received German citizenship upon arrival and, for legal reasons, were limited in their choice of place of residence, we do not include them in the construction of our instrumental variable. For details, see Glitz (2011).

[18]The remaining shares for the native German population are 64.4% with intermediate education and 10.4% with high education levels. All figures are based on the German Microcensus 1995.

origin.

Using the 1973 industry classification provided in the IAB data, we distinguish 44 two-digit industries that produce tradable goods.[19] Following Hanson and Slaughter (2002), we include the following sectors in the group of tradable industries: manufacturing, agriculture, mining, finance, real estate, business services and legal services. For a detailed overview of the individual industries and a number of key indicators see Table A-1 in the appendix. As shown in column (1) of that table, the biggest tradable industry in 1995 was *Manufacturing of electrical equipment* with around 812,000 employees, which corresponded to 9.9% of the overall full-time employment in the tradable sector in that year. Overall employment declined by 3.2% to around 8,2 million between 1985 and 1995 but the variation in employment growth across industries was substantial, ranging from a decrease of 51.0% in *Manufacture of apparel* to an increase of 68.5% in *Architecture and engineering firms*.

Table 2 provides some information about the firms in our data. Overall, there are 402,539 firms operating in the 44 tradable industries in the 204 labor market regions in 1995. About half of these firms already existed in 1985 ("permanent firms"), while another half are firms that were newly established in the ten years between 1985 and 1995. As one would expect, permanent firms are typically larger than both new and old firm, with 30.9 full-time employees on average in 1995, compared to 9.0 employees in new firms in the same year and 11.0 employees in old firms in 1985. The average firm size is 23.4 workers in 1985 which declined by 12.3% to 20.5 employees in 1995. In 1985, 33.5% of workers employed in these firms are low-skilled, 61.3% medium-skilled, and 5.2% high-skilled.[20] In the decade thereafter, the share of low-skilled workers dropped by 28.1% to 24.1%, the share of medium-skilled workers increased slightly by 9.9% to 67.4%, and the share of high-skilled workers increased substantially by 64.3% to 8.5%. The substantial overall shift in skill shares towards more highly educated workers reflects the secular increases

[19]Based on this industry classification, there are 35 industries that produce non-tradable goods. Due to small numbers of observations, the following two-digit industries in the 1973 industry classification were pooled: 5-8, 9-11, 17/18, 23/24, 28/29, 31/32, 35/36, 47-51, 57/58, and 93/94.

[20]The share of college educated workers in the IAB data is lower than the corresponding figure from the Microcensus because self-employed individuals and civil servants, many of whom have a college degree, are not included in these data.

Table 2: Characteristics of firms in tradable sector

	1985	1995	Change
No. of firms	364,703	402,539	10.4
No. permanent firms		210,748	
No. new firms		191,791	
No. old firms †	153,955		
Average size	23.4	20.5	-12.3
Average size permanent firms		30.9	
Average size new firms		9.0	
Average size old firms	11.0		
% low skill	33.5	24.1	-28.1
% medium skill	61.3	67.4	9.9
% high skill	5.2	8.5	64.3
Wage low skill	54.8	63.9	16.7
Wage medium skill	72.5	83.2	14.8
Wage high skill	110.9*	129.9*	17.1*

Notes: Wages are median wages of each skill group. A (*) indicates that the median wage suffers from right censoring, that is that more than 50% of the individuals in that group had wages above the taxable base so that the table entry is simply the value of the censoring limit in the corresponding year. For the wage changes, a (*) indicates that in at least one of the years 1985 and 1995, the median wage lay above the taxable base so that the percentage change is not accurate.
† The number of old firms refers to the number of firms that existed in 1985 but do not exist anymore in 1995.

in both high-skill labor supply (due to higher college graduation rates) and high-skill labor demand (due to, for example, skill-biased technological change) which can also be observed in many other developed economies throughout the 1980s and 1990s. In our estimation, we include a full set of skill fixed effects to account for these secular trends. Despite the significant changes in relative factor inputs, median wage growth between 1985 and 1995 was quite similar across skill groups, increasing by 16.7% for low-skilled workers, 14.8% for medium-skilled workers, and 17.1% for high-skilled workers.

4 Results

4.1 Wage Responses

In Table 3, we show estimates of Equation (5), reporting the wage response γ to labor supply shocks across regions over the period 1985 to 1995. The estimates can be inter-

Table 3: Wage impact of changes in skill-specific employment in the tradable sector

	Tradable Industries				Non-tradable Industries			
	Education groups 1 - 3		Education groups 1 - 2		Education groups 1 - 3		Education groups 1 - 2	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\hat{\gamma}$	0.006	-0.085	0.006	-0.091	-0.145*	-0.490***	-0.231	-0.594***
	(0.049)	(0.069)	(0.054)	(0.069)	(0.080)	(0.151)	(0.142)	(0.181)
F-stat 1^{st} stage		8.48		6.35		20.09		6.71
Observations	458	458	408	408	593	593	408	408

Notes: Dependent variable is the change in the median wage of each skill group. For columns (1), (2), (5) and (6) observations are only included if the median wage is not censored. Robust standard errors are reported in parentheses and are clustered on the regional level. Regressions are weighted by $(1/N_i^{85} + 1/N_i^{95})^{-1/2}$ where N_i^t represents the regional employment in skill group i in year t based on which the median wages are calculated. A (*) denotes statistical significance at the 10% level, a (**) at the 5% level and a (***) at the 1% level.

preted as the percentage response of relative skill-group specific wages to a one percent increase in skill-group specific labor supply. The first four columns report results for the tradable industries (which are the industries we focus on the subsequent analysis) while the remaining columns report results for non-tradable industries.

For tradable industries, the OLS results in columns (1) and (3) show that there is no effect of changes in relative skill-specific labor supply on relative wages both using all three skill groups and using only low- and medium-skilled workers. Columns (2) and (4) report IV results, using the supply-push component of immigration as an instrument for the percentage change in skill-specific labor supply. The first stage regression is reasonably strong in both estimations with F-statistics for the instrument of 8.48 and 6.35. Both estimates, although more negative than the OLS estimates, show no significant impact of changes in relative labor supply on relative wages. The wage elasticity is estimated at -0.085 using all three education groups and -0.091 using only medium- and low-skilled workers. We thus conclude that immigration over that period had no effect on regional wages of workers who are employed in the tradable sector. In columns (5) to (8), we report the same estimates for the non-tradable sector. Here results are quite different: OLS as well as IV regressions show that changes in local labor supply had a significant negative

impact on wages of workers in those skill groups that experienced the supply increases. For instance, results in column (6) suggest that a 1 percent increase in labor supply of a particular skill group due to immigration leads to a decrease in relative median wages for workers in that skill group of about 0.49 percent. Hence, these findings suggest that immigration affected wages in the non-tradable sector, but not in the tradable sector.[21]

These findings are interesting as they suggest that the impact of immigration on wages should be sought in the non-tradable rather than the tradable sector. Our study is the first we are aware of that draws this distinction when estimating the wage impacts of immigration. For the subsequent analysis, however, the main result from Table 3 is the absence of any significant effect of changes in local labor supply on wages in the tradable sector. This suggests that in that sector, adjustments may have taken place through other mechanisms than factor prices. This is what we investigate next.

4.2 Responses on the Firm level

To start with, we decompose the adjustment to relative labor supply changes into between and within firm adjustments and the net contribution of new firms, as presented in Equation (3). Table 4 presents our results. In the Table, we report OLS results in the upper panel and IV results in the lower panel. IV estimates use the predicted immigrant inflow to instrument the potentially endogenous changes in employment levels in a locality.

Our OLS results suggest that changes in the scale of firms that use the more abundant factor more intensively absorb 21.3% of the relative changes in local employment. In comparison, changes within firms towards technologies that use the more abundant factor more intensively absorb 32.2% of the overall employment changes. Another 27.2% are explained by the net contribution of new firms, and the remaining 19.3% cannot be

[21] We could in principle estimate wage equations on the level of the firm. When we do that, our results reflect those obtained from the regressions on the regional level. There is no evidence of a strong effect of changes in relative skill-specific employment on relative wages. However results from the firm-level regressions do not identify the elasticity of substitution between the different skill groups within firms since they do not take account of the potential endogeneity of the changes in firm-specific relative factor inputs. Moreover, under the reasonable assumption that labor is mobile between firms, changes in firm-specific relative factor inputs are not expected to lead to changes in relative wages since these are determined at the labor market rather than the firm level.

Table 4: Decomposition of changes in labor supply on the firm level, only tradable firms

Permanent Firm Scale Effect	Permanent Firm Intensity Effect	Permanent Firm Residual Term	Net New Firm Contribution
	OLS		
0.213***	0.322***	0.193***	0.272***
(0.025)	(0.042)	(0.041)	(0.024)
	IV		
0.044	0.700***	0.076	0.181***
(0.052)	(0.134)	(0.099)	(0.062)

Notes: All regressions use 612 observations and include a full set of skill and region fixed effects. Robust standard errors are reported in parentheses. Regressions are weighted by $(1/N_r^{85} + 1/N_r^{95})^{-1/2}$ where N_r^t represents overall employment in tradable industries in region r in year t. The first stage F-stat of the instrument is 35.02. A (*) denotes statistical significance at the 10% level, a (**) at the 5% level and a (***) at the 1% level.

unambiguously assigned.[22] These findings seem to support the main result in the earlier industry-based literature that within-adjustments are more important than between adjustments. However they also emphasize that new firms play an important role in the absorption process.

As we discuss above, these results have a purely descriptive interpretation, as they are not able to reveal the direction of causality. They are nevertheless important and interesting, as they explain the overall absorption of changes in skill-specific labor supply across regions. The second row of Table 4 presents IV results, which use predictions of the inflows of immigrants into particular regions as instruments for local employment changes (see Appendix C for further explanations). The results show that now only 4.4% of the change in skill-specific employment is absorbed by an increase in the scale of permanent firms, while 70.0% is absorbed by changes in relative factor intensities, and another 18.1% by the net contribution of new firms.[23] The absorption of exogenously allocated workers to areas thus seems to take place predominantly within firms through the use of production technologies that use the more abundant factor more intensively. The relatively large scale effect estimated in the OLS specification, in contrast, seems to reflect scale expansions of

[22]This residual term is often implicitly assigned in equal shares to the scale and intensity effects by evaluating the corresponding changes at the mean of the first and last period (see, for example, Autor et al., 1998, and Hanson and Slaughter, 2002).

[23]Notice that this decomposition relates only to adjustments to labor supply shifts explained by our instruments, and that in each row the estimates have to sum up to one by construction.

firms attracting workers into the specific labor market rather than a mechanism to absorb exogenous changes in labor supply in a particular area. Finally, the net new firm effect remains important in the IV estimation, suggesting a substantial role for firm creation in the overall absorption process.[24]

4.3 Quantifying the Aggregation Bias

How do these results compare to those one would find on the industry level, following the approach by, for example, Lewis (2003)? To investigate this, we estimate models on the industry level as explained in Section 2.3. We use the industry classification presented in Table A-1 and report results in Table 5. As before, the upper panel contains OLS results, the lower panel IV results. The first row in each panel presents industry scale effects and industry intensity effects, following the decomposition shown in Equation (4). The OLS results show that 16.6% of the changes in skill-specific employment in tradable industries are absorbed by differential growth in the scale of the industries, while 58.5% are absorbed through changes in the relative factor intensities within industries. The IV estimates in the second panel suggest that labor supply shocks induced by immigration are mainly absorbed within industries (to 89.9%), while the between industry (scale) absorption is only 2.8%. These results are very much in accordance with Lewis' (2003) findings for the U.S. and González and Ortega's (2011) findings for Spain, who estimate the adjustment within industries to be around 74% and 60%, and the adjustment between industries to be around 4% and 7%, respectively.[25] They also confirm the finding of Hanson and Slaughter (2002) that within industry changes in production technique play a key part in absorbing changes in local labor supplies. Overall, results on the industry level suggest that only a relatively small fraction of the changes in labor supply are absorbed by an expansion of those industries that use the more abundant factor more intensively as predicted by the

[24]Recent work by Beaudry et al. (2011) provides evidence for a proportional relationship between the size of the local population and the number of job creators. Part of the net new firm adjustment we measure could thus arise from recent immigrant arrivals setting up new firms themselves.

[25]Note, however, that the figures are not directly comparable as both aforementioned papers decompose changes in the entire skill-specific labor force in a region, including both changes in non-tradable industries and changes in the number of unemployed individuals. If we follow this approach, the corresponding figures are 70.7% for the within adjustment and 17.4% for the between adjustment.

Table 5: Decomposition of changes in labor supply on the industry level vs firm level

Industry Scale Effect			Industry Intensity Effect			
Permanent Firm Scale Effect	Net New Firm Scale Effect	Aggregation Bias	Permanent Firm Intensity Effect	Net New Firm Intensity Effect	Aggregation Bias	Residual Term
			OLS			
	0.166***			0.585***		0.249***
	(0.016)			(0.025)		(0.022)
0.213***	0.054	-0.102**	0.322***	0.218***	0.046	0.193***
(0.025)	(0.047)	(0.046)	(0.042)	(0.049)	(0.061)	(0.041)
			IV			
	0.028			0.899***		0.074
	(0.059)			(0.072)		(0.048)
0.044	0.144	-0.160	0.700***	0.037	0.162	0.076
(0.052)	(0.129)	(0.118)	(0.134)	(0.112)	(0.161)	(0.099)

Notes: The residual terms reported in the last column refer to the industry residual term in the upper row of each panel, and the permanent firm residual term in the lower row of each panel. All regressions use 612 observations and include a full set of skill and region fixed effects. Robust standard errors are reported in parentheses. Regressions are weighted by $(1/N_r^{85} + 1/N_r^{95})^{-1/2}$ where N_r^t represents overall employment in tradable industries in region r in year t. The first stage F-stat is 35.02. A (*) denotes statistical significance at the 10% level, a (**) at the 5% level and a (***) at the 1% level.

traditional Heckscher-Ohlin-Samuelson model.

In the second row of the OLS panel in Table 5, we report the results of the decomposition of industry-level scale and intensity effects, when moving down to the firm level (compare Equations (5) and (6)). Consider first the results for the scale effect. The fact that the permanent firm scale effect is larger than the industry scale effect (21.3% vs. 16.6%) and the net scale contribution of new firms is positive (5.4%), suggests that there is a considerable aggregation bias, as summarized by the negative bias term (-10.2%). Closer inspection of the individual components of this bias term (see Appendix B-4) reveals that the bias on the aggregate industry level is predominantly due to the fact that within industries, firms that use the more abundant factor more intensively grow faster than firms that do not (see our discussion in Section 2.3).[26] These differential growth rates of firms lead, collectively, to a shift in factor intensities in an industry towards the more abundant factor. In a traditional industry level analysis, such a shift would then be

[26]The contributions of permanent and net new firms to the aggregation bias term for the scale effect are -11.8% and 1.6%, respectively.

erroneously interpreted as an adjustment in production technology.

For the within-industry effect, the aggregation bias is close to zero (4.6%), but the decomposition to the firm level shows that around 37% (21.8%/58.5%) of the adjustment to skill-specific employment changes within industries takes place through the net creation of new firms, by either new firms entering with a technology that is, relative to the industry average, intensive in the use of the abundant factor or by new firms changing their production technology over time after entry. Overall, these results suggests that the net creation of new firms is an important absorption mechanism for skill-specific changes in local labor supply.

In the second row of the lower panel in Table 5, we report the IV results from the firm level analysis. These suggest that the small effects estimated on the industry level (2.8%) obscure the fact that on the firm level, the net new firm effect is absorbing a substantial part (14.4%) of the exogenous local labor supply shocks (although it is not precisely estimated). The industry decomposition is unable to detect this effect. Thus, one way to interpret these findings is that scale adjustments to labor supply shocks may indeed take place, but that they occur through new firms being created that use the more abundant factor more intensively, rather than through scale adjustments in already existing firms. The within-industry effect is largely accounted for by adjustments within firms that are permanent, i.e. that are observed both at the beginning and the end of the observation period, whereas the net new firm effect is relatively unimportant, accounting for only 4.1% (3.7%/89.9%) of the within industry adjustment in relative factor supplies.

4.4 Extensions

We now carry out a few additional extensions to the standard decomposition. First of all, we distinguish between the contributions of small and large firms. We define small firms as those with at most 100 full-time employees in the base year 1985 (for new firms, the size limit refers to the year 1995). There are 1,241,971 small firms with on average 6.8 workers and 23,344 large firms with on average 379.7 workers operating in Germany in 1985. Overall full-time employment is thus roughly shared equally between these two

Table 6: Decomposition of changes in labor supply on the firm level, extensions

	Permanent Firm Scale Effect	Permanent Firm Intensity Effect	Permanent Firm Residual Term	Net New Firm Contribution
Large Firms		**OLS**		
	0.109***	0.161***	0.163***	0.082***
	(0.022)	(0.042)	(0.038)	(0.023)
		IV		
	0.027	0.393***	0.037	0.016
	(0.040)	(0.136)	(0.096)	(0.045)
Small Firms		**OLS**		
	0.104***	0.161***	0.030*	0.190***
	(0.018)	(0.017)	(0.017)	(0.016)
		IV		
	0.016	0.308***	0.037	0.166***
	(0.027)	(0.043)	(0.026)	(0.035)
		Idiosyncratic	Nationwide	
Nationwide		**OLS**		
	0.213***	0.259***	0.062***	0.193***	0.272***
	(0.025)	(0.043)	(0.017)	(0.041)	(0.024)
			IV		
	0.044	0.577***	0.123***	0.076	0.181***
	(0.052)	(0.134)	(0.042)	(0.099)	(0.063)

Notes: All regressions include a full set of skill and region fixed effects. The number of observations is 609 in Panel A and 612 in Panels B and C. Robust standard errors are reported in parentheses. Regressions are weighted by $(1/N_r^{85} + 1/N_r^{95})^{-1/2}$ where N_r^t represents overall employment in tradable industries in region r in year t. The first stage F-stat is 34.45 in Panel A and 35.02 in Panels B and C. A (*) denotes statistical significance at the 10% level, a (**) at the 5% level and a (***) at the 1% level.

groups of firms (48.8% vs. 51.2%). The first two panels in Table 6 show the results of our firm-level decomposition (Equation (3)), for small and large firms separately. Both in the OLS and the IV estimations, the relative adjustment through changes in scale and factor intensities is remarkably similar for both types of firms. As expected, the main difference lies in the contribution through the net creation of new firms. Since only very few newly created or exiting firms are large, their contribution to the absorption of changes in local factor supplies is small, around 8.2% in the OLS and 1.6% in the IV estimations. Small new firms, on the other hand, contribute a significant share of 19.0% and 16.6%, respectively, to the absorption.

In the third panel of the table, we report results where we remove nationwide industry-specific changes in intensity adjustments in Equation (3). Hanson and Slaughter (2002) argue that these cannot be interpreted as being a response to changes in local labor supply. To do that, we first calculate for each industry and skill group the nationwide percentage change in factor intensity, $\%\Delta^N(\frac{N_{ij}}{M_j})$, and then subtract this change from the actual change in each permanent firm to obtain the component of the change in relative factor intensities that is idiosyncratic to each firm in a given region, $\%\Delta^I(\frac{N_{ijf}}{M_{jf}})$:

$$\%\Delta^I(\frac{N_{ijf}}{M_{jf}}) = \%\Delta(\frac{N_{ijf}}{M_{jf}}) - \%\Delta^N(\frac{N_{ij}}{M_j}).$$

Substituting this equality into Equation (3) leads to a new decomposition of the within industries effect into a component due to nationwide changes in factor intensities and an idiosyncratic region-specific component. The estimates in the third panel in Table 6 shows that in Germany the latter plays the dominant role: in the IV estimations, 57.7 percentage points of the original 70.0% can be attributed to such idiosyncratic changes in relative factor intensities, which means that firms in the same industries operating in different regions change their relative factor inputs differentially in response to local changes in factor supplies. Only 12.3% of the adjustment to changes in local labor supply can be attributed to nationwide changes in industry-specific relative factor intensities.

5 Summary and Conclusion

This paper analyzes three channels by which local labor markets and the production units operating therein can absorb skill-specific changes in labor supply: Factor prices, between-production unit scale adjustments, and within-production unit factor intensity adjustments. In contrast to previous work, we investigate the different adjustment channels on the level of the firm, which eliminates possible aggregation bias and allows an assessment of the contribution of new and dying firms. To isolate the causal effect of local supply shocks from demand driven supply changes, we instrument potentially endogenous changes in local labor supply with the inflows of immigrants that are driven by

past settlement patterns of their co-nationals.

In a first step, we analyze the effect of changes in local labor supply on skill-specific wages, using data for 204 local labor markets in Germany over the period 1985 to 1995. Although we find significant wage responses in the non-tradable sector, there are no wage effects in the tradable sector, even if we instrument labor supply changes with predicted immigrant-induced labor supply shocks. This suggests that a distinction between tradable and non-tradable sectors is important for studies that investigate factor price responses to immigration.

Focussing on the tradable sector, we find that labor supply changes are associated with both scale adjustments of firms and within-firm adjustments in relative factor intensities, with the first association being smaller in magnitude. In addition, we find that an important further adjustment mechanism is the creation and destruction of firms.

These overall adjustments could be driven by responses to unforeseen supply shifts or by demand-driven supply responses. To isolate the responses to supply shifts, we again exploit immigration-induced changes in relative skill supplies. We find that more than two thirds of the changes in local labor supply due to supply shocks are absorbed by within-firm changes in relative factor intensities. Given that relative factor prices are constant, this points towards changes in production technology as an important adjustment mechanism to labor supply shocks. Scale (between firm) adjustments are small in magnitude, which indicates that the scale effects estimated in standard OLS regressions are likely the result of demand driven changes in factor supplies, through workers responding to job opportunities created by expanding firms.

The creation and destruction of firms plays an important role in the overall adjustment to local supply shocks. New firms enter in industries and with relative factor intensities that are conducive to the absorption of the factor that has become relatively more abundant as a result of immigration. Comparing results from an industry-level analysis with those from the firm-level analysis, we find that the former understates the relative contribution of scale adjustments as it does not take account of the heterogeneity of firms within an industry and the contribution of new and old firms. Further, while the relative im-

portance of the different adjustment channels on the firm level does not vary significantly for existing firms of different sizes, the absorption through firm turnover is predominantly due to small firms entering and exiting the labor market. Finally, nationwide changes in industry-specific relative factor intensities can only explain a small fraction of the overall adjustment through changes in relative factor intensities, pointing towards firms implementing production technologies in direct response to the labor supply conditions they are facing in their local labor market.

Our analysis sheds light on the important question of how regional labor markets adjust to changing labor supply conditions. The results suggest that changes in factor prices are only one – and as it turns out relatively unimportant – mechanism to equalize labor demand and labor supply in the tradable sector in a local market. Rather than focussing exclusively on this last mechanism, as most of the existing literature has done, this study calls for a more comprehensive approach to fully understand the complexities of local adjustment processes, giving particular emphasis to firms' technology choices and the creation of new firms as key channels.

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Appendix A Industry characteristics

Table A-1: Tradable industry characteristics

Industry	1995									Change 1985 - 1995			
	Total employ-ment	% share employ-ment	Average firm size	% low skill	% medium skill	% high skill	Wage low skill	Wage medium skill	Wage high skill	%Δ employ-ment	%Δ low skill	%Δ medium skill	%Δ high skill
All	8,244,637	100.0	20.5	24.1	67.4	8.5	63.9	83.2	129.9	−3.2	−28.1	9.9	64.3
Manufacture of electrical equipment	812,428	9.9	49.3	25.4	60.8	13.8	64.1	83.8	129.9	−7.9	−28.3	10.8	42.0
Financial intermediation and insurance industry	763,728	9.3	24.3	13.0	78.1	8.9	57.5	95.0	128.7	11.4	−28.9	1.8	76.5
Manufacture of motor vehicles	590,164	7.2	283.5	25.6	67.1	7.4	82.8	94.5	129.9	−8.6	−33.0	16.5	71.6
Manufacture of machinery	543,740	6.6	42.6	15.4	76.7	7.9	64.6	87.6	129.9	−8.2	−34.0	6.7	65.1
Manufacture of chemicals and chemical products	498,944	6.1	139.8	21.0	66.8	12.2	73.9	96.9	129.9	−11.4	−32.1	9.9	47.7
Legal advice and business consulting	350,270	4.2	5.9	14.5	66.9	18.6	17.9	66.0	118.9	68.0	−33.4	−1.0	74.9
Manufacture of earth-moving equipment	345,738	4.2	40.1	35.1	61.4	3.5	64.8	79.1	129.9	2.6	−20.3	13.7	79.9
Architecture and engineering firms	311,192	3.8	7.4	8.2	57.4	34.5	33.1	83.0	122.7	68.5	−29.7	−7.2	29.7
Manufacture of food products	305,622	3.7	14.4	29.4	68.4	2.2	52.1	62.8	129.7	−2.1	−25.9	15.7	83.2
Manufacture of furniture	294,588	3.6	10.8	25.9	72.8	1.4	54.9	73.5	106.3	6.3	−14.1	5.3	72.5
Manufacture of gears	291,711	3.5	55.2	19.3	72.0	8.7	67.1	85.5	129.9	−9.1	−27.3	7.4	35.5
Manufacture of plastic products	269,660	3.3	40.4	37.5	58.7	3.8	61.6	76.0	129.0	23.6	−20.3	15.7	70.7
Printing	184,593	2.2	16.1	22.1	75.3	2.6	64.5	88.1	123.1	1.3	−15.7	4.1	78.9
Manufacture of tanks and containers	178,776	2.2	25.3	18.3	76.1	5.6	65.7	80.5	129.9	5.4	−21.7	4.4	49.7
Manufacture of stones and mortars	177,211	2.1	18.4	29.9	66.3	3.8	75.1	84.3	129.9	2.0	−20.2	10.7	46.3
Precision mechanics and optical equipment	173,993	2.1	14.7	23.8	70.2	6.0	52.4	75.9	129.9	−6.4	−29.0	11.7	65.2
Real estate	165,129	2.0	5.6	12.1	75.5	12.4	54.4	83.3	129.9	66.1	−24.6	0.7	37.8
Manufacture of basic iron and steel	163,601	2.0	217.6	32.6	62.2	5.2	74.2	84.5	129.9	−37.0	−19.8	11.7	41.4
Manufacture of ventilation and heating equipment	159,386	1.9	10.9	17.9	78.9	3.2	18.1	74.7	123.5	20.7	−20.7	5.3	29.5
Manufacture of paper products	142,114	1.7	55.8	37.7	58.7	3.6	65.6	81.3	129.9	−0.6	−22.6	19.6	63.4
Meat processing	140,148	1.7	8.7	27.1	72.3	0.5	46.8	57.1	109.6	−14.7	−27.0	15.6	80.3
Forging, stamping and pressing of steel	136,654	1.7	26.5	37.3	60.1	2.5	67.0	80.0	129.9	3.5	−17.4	13.1	55.4
Manufacture of textiles	133,834	1.6	39.5	43.1	53.9	3.0	56.3	70.6	115.7	−39.8	−21.3	23.3	94.0
Mining and quarrying	129,766	1.6	299.0	29.9	62.9	7.2	74.6	82.3	129.9	−41.9	−12.4	3.7	39.0
Manufacture of apparel	88,201	1.1	17.7	33.2	65.1	1.8	46.1	56.5	97.4	−51.0	−24.7	17.6	183.9
Manufacture of beverages and tobacco products	87,948	1.1	35.2	23.9	71.9	4.2	68.8	84.3	129.9	−16.1	−20.5	6.9	56.0
Shipbuilding and manufacture of aircraft	83,385	1.0	129.1	12.0	71.1	16.8	70.7	93.4	129.9	−13.8	−36.1	3.3	36.8
Casting of metals	81,413	1.0	67.5	41.2	55.9	2.9	74.1	84.8	129.9	−19.7	−15.4	12.9	66.3
Locksmith's, grinding and welding shops	77,191	0.9	6.9	21.1	77.4	1.5	47.9	69.7	110.9	18.3	−30.4	12.4	81.3
Manufacture of rubber products	76,593	0.9	76.8	39.4	54.6	6.0	70.4	78.8	129.9	−22.3	−21.3	16.9	86.7
Advertising	66,123	0.8	5.7	14.6	74.6	10.8	44.6	78.4	102.6	65.4	−20.3	0.0	51.7
Manufacture of glass products	60,239	0.7	63.7	35.6	59.5	4.9	66.3	76.5	129.9	−8.6	−25.3	19.7	85.4
Manufacture of wood	57,154	0.7	18.0	43.8	54.4	1.9	62.5	75.4	116.7	−0.5	−13.4	12.4	68.1
Manufacture of ceramic products	47,962	0.6	46.3	47.1	48.9	3.9	57.7	71.5	129.9	−19.1	−16.7	18.7	77.1
Manufacture of data processing equipment	42,258	0.5	34.1	17.0	62.1	20.9	65.6	94.7	129.9	−39.5	−34.3	12.3	10.9
Manufacture of confectionery	41,894	0.5	99.7	48.0	48.6	3.5	49.2	76.7	129.9	5.8	−10.3	8.7	86.8
Cold drawing and rolling	40,234	0.5	86.2	41.0	55.6	3.4	73.7	84.4	129.9	−23.3	−17.1	14.5	71.2
Manufacture of other wood products	31,469	0.4	14.8	44.2	54.3	1.5	57.5	69.9	110.0	−1.4	−13.0	12.7	47.1
Manufacture of footwear	24,400	0.3	10.4	42.2	55.1	2.7	52.3	62.1	117.6	−48.1	−29.8	40.2	389.0
Manufacture of toys and musical instruments	19,656	0.2	18.4	39.6	58.3	2.1	53.9	71.6	109.5	−14.1	−17.9	15.2	79.9
Upholstery	18,040	0.2	5.7	30.0	69.2	0.8	47.3	60.9	88.8	6.4	−12.9	6.6	23.8
Manufacture of leather products	16,533	0.2	14.6	42.8	55.3	1.9	49.5	63.5	112.0	−36.9	−20.6	22.1	138.0
Manufacture of jewellery	15,198	0.2	7.2	25.6	73.2	1.3	45.1	63.5	107.4	−21.7	−24.2	11.9	36.9
Agriculture	5,756	0.1	4.1	30.3	64.3	5.4	37.6	60.5	106.7	14.1	−24.4	14.6	41.4

Notes: The employment growth is calculated using all full-time employees, including those with missing information for the educational attainment. The skill shares are calculated relative to the overall workforce with observed educational attainment.

Appendix B Decompositions

Appendix B-1 Firm-level Decomposition

The change in skill-specific employment in all tradable industries j in a local labor market is given by:

$$\begin{aligned}\Delta N_i &= \sum_j \Delta N_{ij} \\ &= \sum_j (\sum_{f\in\mathcal{N}^p} \Delta N_{ijf} + \sum_{f\in\mathcal{N}^n} \Delta N_{ijf} + \sum_{f\in\mathcal{N}^o} \Delta N_{ijf}).\end{aligned}$$

Dividing through by the total employment of skill group i in the base period (denoted by the subscript 0) and then expanding we get

$$\begin{aligned}\frac{\Delta N_i}{N_{i_0}} &= \sum_j (\sum_{f\in\mathcal{N}^p} \frac{\Delta N_{ijf}}{N_{i_0}} + \sum_{f\in\mathcal{N}^n} \frac{\Delta N_{ijf}}{N_{i_0}} + \sum_{f\in\mathcal{N}^o} \frac{\Delta N_{ijf}}{N_{i_0}}) \\ &= \sum_j \sum_{f\in\mathcal{N}^p} \frac{N_{ijf_0}}{N_{i_0}} \frac{\Delta N_{ijf}}{N_{ijf_0}} + \sum_j \sum_{f\in\mathcal{N}^n} \frac{\Delta N_{ijf}}{N_{i_0}} + \sum_j \sum_{f\in\mathcal{N}^o} \frac{N_{ijf_0}}{N_{i_0}} \frac{\Delta N_{ijf}}{N_{ijf_0}} \\ &= \sum_j \sum_{f\in\mathcal{N}^p} s_{ijf_0} \%\Delta N_{ijf} + \sum_j \sum_{f\in\mathcal{N}^n} \frac{N_{ijf}}{N_{i_0}} - \sum_j \sum_{f\in\mathcal{N}^o} \frac{N_{ijf_0}}{N_{i_0}},\end{aligned} \tag{B-1}$$

where $s_{ijf_0} = \frac{N_{ijf_0}}{N_{i_0}}$.

Now let M_{jf} be a measure of the size of a firm. For all permanent firms we can be decomposed the first term of Equation (B-1) into the following three terms:

$$\begin{aligned}\%\Delta N_{ijf} = \frac{\Delta N_{ijf}}{N_{ijf_0}} &= \frac{M_{jf}N_{ijf}}{N_{ijf_0}M_{jf}} - \frac{M_{jf_0}N_{ijf_0}}{N_{ijf_0}M_{jf_0}} = \frac{M_{jf}N_{ijf}}{N_{ijf_0}M_{jf}} - 1 \\ &= \frac{N_{ijf}M_{jf_0}}{M_{jf}N_{ijf_0}} + \frac{(M_{jf}-M_{jf_0})N_{ijf}}{M_{jf}N_{ijf_0}} - 1 \\ &= \frac{M_{jf}-M_{jf_0}}{M_{jf_0}} + \frac{N_{ijf}M_{jf_0}}{M_{jf}N_{ijf_0}} - 1 + \frac{M_{jf}-M_{jf_0}}{M_{jf_0}}\left(\frac{N_{ijf}M_{jf_0}}{M_{jf}N_{ijf_0}} - 1\right) \\ &= \left(\frac{M_{jf}-M_{jf_0}}{M_{jf_0}}\right) + \left(\frac{\frac{N_{ijf}}{M_{jf}} - \frac{N_{ijf_0}}{M_{jf_0}}}{\frac{N_{ijf_0}}{M_{jf_0}}}\right) + \left(\frac{M_{jf}-M_{jf_0}}{M_{jf_0}}\right)\left(\frac{\frac{N_{ijf}}{M_{jf}} - \frac{N_{ijf_0}}{M_{jf_0}}}{\frac{N_{ijf_0}}{M_{jf_0}}}\right) \\ &= \%\Delta M_{jf} + \%\Delta\left(\frac{N_{ijf}}{M_{jf}}\right) + \%\Delta M_{jf} \cdot \%\Delta\left(\frac{N_{ijf}}{M_{jf}}\right).\end{aligned}$$

Plugging this expression into Equation (B-1) yields the basic firm level decomposition given in Equation (3).

Appendix B-2 New/Old Firm Decomposition

The terms involving new and old firms can be decomposed in the following way:

$$\begin{aligned}
\sum_j \sum_{f\in\mathcal{N}^n} \frac{N_{ijf}}{N_{i_0}} &= \sum_{t=1}^{T}\sum_j \sum_{f\in\mathcal{N}_t^n} \frac{N_{ijf_t}}{N_{i_0}} + \sum_{t=1}^{T}\sum_j \sum_{f\in\mathcal{N}_t^n} \frac{\Delta_t^T N_{ijf_t}}{N_{i_0}} \\
&= \sum_{t=1}^{T}\Bigg(\sum_j \sum_{f\in\mathcal{N}_t^n} \left(\frac{N_{ij_t}}{N_{i_0}}\right)\left(\frac{M_{jf_t}}{M_{j_t}}\right) + \sum_j \sum_{f\in\mathcal{N}_t^n} \left(\frac{N_{ij_t}}{N_{i_0}}\right)\left(\frac{M_{jf_t}}{M_{j_t}}\right)\left(\frac{\frac{N_{ijf_t}}{M_{jf_t}} - \frac{N_{ij_t}}{M_{j_t}}}{\frac{N_{ij_t}}{M_{j_t}}}\right)\Bigg) \\
&+ \sum_{t=1}^{T}\Bigg(\sum_j \sum_{f\in\mathcal{N}_t^n} \frac{N_{ijf_t}}{N_{i_0}} \frac{\Delta_t^T N_{ijf_t}}{N_{ijf_t}}\Bigg) \\
&= \underbrace{\sum_{t=1}^{T}\sum_j \sum_{f\in\mathcal{N}_t^n} \left(\frac{N_{ij_t}}{N_{i_0}}\right)\left(\frac{M_{jf_t}}{M_{j_t}}\right)}_{\text{new firm entry scale}} + \underbrace{\sum_{t=1}^{T}\sum_j \sum_{f\in\mathcal{N}_t^n} \left(\frac{N_{ij_t}}{N_{i_0}}\right)\left(\frac{M_{jf_t}}{M_{j_t}}\right)\left(\frac{\frac{N_{ijf_t}}{M_{jf_t}} - \frac{N_{ij_t}}{M_{j_t}}}{\frac{N_{ij_t}}{M_{j_t}}}\right)}_{\text{new firm entry intensity}} \\
&+ \underbrace{\sum_{t=1}^{T}\sum_j \sum_{f\in\mathcal{N}_t^n} \frac{N_{ijf_t}}{N_{i_0}} \%\Delta_t^T M_{jf_t} + \frac{1}{2}\sum_{t=1}^{T}\sum_j \sum_{f\in\mathcal{N}_t^n} \frac{N_{ijf_t}}{N_{i_0}} \%\Delta_t^T M_{jf_t} \%\Delta_t^T \left(\frac{N_{ijf_t}}{M_{jf_t}}\right)}_{\text{new firm growth scale}} \\
&+ \underbrace{\sum_{t=1}^{T}\sum_j \sum_{f\in\mathcal{N}_t^n} \frac{N_{ijf_t}}{N_{i_0}} \%\Delta_t^T \left(\frac{N_{ijf_t}}{M_{jf_t}}\right) + \frac{1}{2}\sum_{t=1}^{T}\sum_j \sum_{f\in\mathcal{N}_t^n} \frac{N_{ijf_t}}{N_{i_0}} \%\Delta_t^T M_{jf_t} \%\Delta_t^T \left(\frac{N_{ijf_t}}{M_{jf_t}}\right)}_{\text{new firm growth intensity}}
\end{aligned}$$

$$\begin{aligned}
\sum_j \sum_{f\in\mathcal{N}^o} \frac{N_{ijf_0}}{N_{i_0}} &= \sum_{t=0}^{T-1}\sum_j \sum_{f\in\mathcal{N}_t^o} \frac{N_{ijf_t}}{N_{i_0}} - \sum_{t=0}^{T-1}\sum_j \sum_{f\in\mathcal{N}_t^o} \frac{\Delta_0^t N_{ijf_t}}{N_{i_0}} \\
&= \sum_{t=0}^{T-1}\Bigg(\sum_j \sum_{f\in\mathcal{N}_t^o} \left(\frac{N_{ij_t}}{N_{i_0}}\right)\left(\frac{M_{jf_t}}{M_{j_t}}\right) + \sum_j \sum_{f\in\mathcal{N}_t^o} \left(\frac{N_{ij_t}}{N_{i_0}}\right)\left(\frac{M_{jf_t}}{M_{j_t}}\right)\left(\frac{\frac{N_{ijf_t}}{M_{jf_t}} - \frac{N_{ij_t}}{M_{j_t}}}{\frac{N_{ij_t}}{M_{j_t}}}\right)\Bigg) \\
&- \sum_{t=0}^{T-1}\Bigg(\sum_j \sum_{f\in\mathcal{N}_t^o} \frac{N_{ijf_0}}{N_{i_0}} \frac{\Delta_0^t N_{ijf_t}}{N_{ijf_0}}\Bigg) \\
&= \underbrace{\sum_{t=0}^{T-1}\sum_j \sum_{f\in\mathcal{N}_t^o} \left(\frac{N_{ij_t}}{N_{i_0}}\right)\left(\frac{M_{jf_t}}{M_{j_t}}\right)}_{\text{old firm exit scale}} + \underbrace{\sum_{t=0}^{T-1}\sum_j \sum_{f\in\mathcal{N}_t^o} \left(\frac{N_{ij_t}}{N_{i_0}}\right)\left(\frac{M_{jf_t}}{M_{j_t}}\right)\left(\frac{\frac{N_{ijf_t}}{M_{jf_t}} - \frac{N_{ij_t}}{M_{j_t}}}{\frac{N_{ij_t}}{M_{j_t}}}\right)}_{\text{old firm exit intensity}} \\
&\underbrace{- \sum_{t=0}^{T-1}\sum_j \sum_{f\in\mathcal{N}_t^o} \frac{N_{ijf_0}}{N_{i_0}} \%\Delta_0^t M_{jf_t} - \frac{1}{2}\sum_{t=0}^{T-1}\sum_j \sum_{f\in\mathcal{N}_t^o} \frac{N_{ijf_0}}{N_{i_0}} \%\Delta_0^t M_{jf_t} \%\Delta_0^t \left(\frac{N_{ijf_t}}{M_{jf_t}}\right)}_{\text{old firm growth scale}} \\
&\underbrace{- \sum_{t=0}^{T-1}\sum_j \sum_{f\in\mathcal{N}_t^o} \frac{N_{ijf_0}}{N_{i_0}} \%\Delta_0^t \left(\frac{N_{ijf_t}}{M_{jf_t}}\right) - \frac{1}{2}\sum_{t=0}^{T-1}\sum_j \sum_{f\in\mathcal{N}_t^o} \frac{N_{ijf_0}}{N_{i_0}} \%\Delta_0^t M_{jf_t} \%\Delta_0^t \left(\frac{N_{ijf_t}}{M_{jf_t}}\right)}_{\text{old firm growth intensity}}
\end{aligned}$$

Note that in both the decomposition for new firms and the decomposition for old firms we have assigned half of the new and old firm growth interaction terms to the corresponding growth scale and growth intensity effects as is common in the literature (e.g. Hanson and Slaughter, 2002).

Appendix B-3 Industry Decomposition

The change in skill-specific employment in all tradable industries j in a local labor market is given by:

$$\Delta N_i = \sum_j \Delta N_{ij}.$$

Dividing through by the total employment of skill group i in the base period (denoted by the subscript 0) and then expanding we get

$$\frac{\Delta N_i}{N_{i0}} = \sum_j \frac{\Delta N_{ij}}{N_{i0}} = \sum_j \frac{N_{ij0}}{N_{i0}} \frac{\Delta N_{ij}}{N_{ij0}} = \sum_j s_{ij0} \%\Delta N_{ij}. \tag{B-2}$$

Let M_j be a measure of the size of an industry. The last term can then be decomposed into three terms:

$$\begin{aligned}
\%\Delta N_{ij} = \frac{\Delta N_{ij}}{N_{ij0}} &= \frac{M_j N_{ij}}{N_{ij0} M_j} - \frac{M_{j0} N_{ij0}}{N_{ij0} M_{j0}} = \frac{M_j N_{ij}}{N_{ij0} M_j} - 1 \\
&= \frac{N_{ij} M_{j0}}{M_j N_{ij0}} + \frac{(M_j - M_{j0}) N_{ij}}{M_j N_{ij0}} - 1 \\
&= \frac{M_j - M_{j0}}{M_{j0}} + \frac{N_{ij} M_{j0}}{M_j N_{ij0}} - 1 + \frac{M_j - M_{j0}}{M_{j0}} \left(\frac{N_{ij} M_{j0}}{M_j N_{ij0}} - 1\right) \\
&= \left(\frac{M_j - M_{j0}}{M_{j0}}\right) + \left(\frac{\frac{N_{ij}}{M_j} - \frac{N_{ij0}}{M_{j0}}}{\frac{N_{ij0}}{M_{j0}}}\right) + \left(\frac{M_j - M_{j0}}{M_{j0}}\right)\left(\frac{\frac{N_{ij}}{M_j} - \frac{N_{ij0}}{M_{j0}}}{\frac{N_{ij0}}{M_{j0}}}\right) \\
&= \%\Delta M_j + \%\Delta\left(\frac{N_{ij}}{M_j}\right) + \%\Delta M_j \cdot \%\Delta\left(\frac{N_{ij}}{M_j}\right),
\end{aligned}$$

which, by substitution into Equation (B-2), yields the stated decomposition.

Appendix B-4 Industry and Firm Level Correspondence

For the scale effect on the industry level we have:

$$
\begin{aligned}
\underbrace{\sum_j s_{ij_0}\%\Delta M_j}_{\text{industry scale effect}} &= \underbrace{\sum_j \sum_{f\in\mathcal{N}^p} s_{ij_0}\left(\frac{M_{jf}-M_{jf_0}}{M_{j_0}}\right)}_{\text{industry scale effect permanent firms}} + \underbrace{\sum_j \sum_{f\in\mathcal{N}^n} s_{ij_0}\left(\frac{M_{jf}}{M_{j_0}}\right)}_{\text{industry scale effect new firms}} - \underbrace{\sum_j \sum_{f\in\mathcal{N}^o} s_{ij_0}\left(\frac{M_{jf_0}}{M_{j_0}}\right)}_{\text{industry scale effect old firms}} \\
&= \underbrace{\sum_j \sum_{f\in\mathcal{N}^p} s_{ijf_0}\cdot\%\Delta M_{jf}}_{\text{permanent firm scale effect}} \\
&+ \underbrace{\sum_{t=1}^{T}\sum_j \sum_{f\in\mathcal{N}_t^n}\left(\frac{N_{ij_t}}{N_{i_0}}\right)\left(\frac{M_{jf_t}}{M_{j_t}}\right) - \sum_{t=0}^{T-1}\sum_j \sum_{f\in\mathcal{N}_t^o}\left(\frac{N_{ij_t}}{N_{i_0}}\right)\left(\frac{M_{jf_t}}{M_{j_t}}\right)}_{\text{net new firm entry scale}} \\
&+ \underbrace{\begin{aligned}&\sum_{t=1}^{T}\sum_j \sum_{f\in\mathcal{N}_t^n}\left(\frac{N_{ijf_t}}{N_{i_0}}\right)\%\Delta_t^T M_{jf_t} + \sum_{t=0}^{T-1}\sum_j \sum_{f\in\mathcal{N}_t^o}\left(\frac{N_{ijf_0}}{N_{i_0}}\right)\%\Delta_0^t M_{jf_t} \\ &+\frac{1}{2}\left(\sum_{t=1}^{T}\sum_j \sum_{f\in\mathcal{N}_t^n}\frac{N_{ijf_t}}{N_{i_0}}\%\Delta_t^T M_{jf_t}\%\Delta_t^T\left(\frac{N_{ijf_t}}{M_{jf_t}}\right)+\sum_{t=0}^{T-1}\sum_j \sum_{f\in\mathcal{N}_t^o}\frac{N_{ijf_0}}{N_{i_0}}\%\Delta_0^t M_{jf_t}\%\Delta_0^t\left(\frac{N_{ijf_t}}{M_{jf_t}}\right)\right)\end{aligned}}_{\text{net new firm growth scale}} \\
&+ \underbrace{\sum_j \sum_{f\in\mathcal{N}^p} s_{ij_0}\left(\frac{M_{jf_0}}{M_{j_0}}-\frac{N_{ijf_0}}{N_{ij_0}}\right)\%\Delta M_{jf}}_{\text{permanent firm bias term scale}} \\
&+ \underbrace{\begin{aligned}&\sum_{t=1}^{T}\sum_j \sum_{f\in\mathcal{N}_t^n}\left[\left(\frac{M_{jf_t}}{N_{i_0}}\right)\left(\frac{N_{ijf_t}}{M_{jf_t}}-\frac{N_{ij_t}}{M_{j_t}}\right)+\left(\frac{M_{jf}+M_{jf_t}}{2N_{i_0}}\right)\left(\frac{N_{ijf}}{M_{jf}}-\frac{N_{ijf_t}}{M_{jf_t}}\right)\right. \\ &\left.-\left(\frac{N_{ij_0}}{N_{i_0}}\right)\left(\frac{N_{ijf}}{N_{ij_0}}-\frac{M_{jf}}{M_{j_0}}\right)\right] \\ &-\sum_{t=0}^{T-1}\sum_j \sum_{f\in\mathcal{N}_t^o}\left[\left(\frac{M_{jf_t}}{N_{i_0}}\right)\left(\frac{N_{ijf_t}}{M_{jf_t}}-\frac{N_{ij_t}}{M_{j_t}}\right)-\left(\frac{M_{jf_t}+M_{jf_0}}{2N_{i_0}}\right)\left(\frac{N_{ijf_t}}{M_{jf_t}}-\frac{N_{ijf_0}}{M_{jf_0}}\right)\right. \\ &\left.+\left(\frac{N_{ij_0}}{N_{i_0}}\right)\left(\frac{M_{jf_0}}{M_{j_0}}-\frac{N_{ijf_0}}{N_{ij_0}}\right)\right]\end{aligned}}_{\text{net new firm bias term scale}}
\end{aligned}
$$

For the intensity effect on the industry level we have:

$$\underbrace{\sum_j s_{ij_0}\left(\frac{\frac{N_{ij}}{M_j}-\frac{N_{ij_0}}{M_{j_0}}}{\frac{N_{ij_0}}{M_{j_0}}}\right)}_{\text{industry intensity effect}} = \underbrace{\sum_j\sum_{f\in\mathcal{N}^p} s_{ij_0}\left(\frac{\frac{N_{ijf}}{M_j}-\frac{N_{ijf_0}}{M_{j_0}}}{\frac{N_{ij_0}}{M_{j_0}}}\right)}_{\text{industry intensity effect permanent firms}} + \underbrace{\sum_j\sum_{f\in\mathcal{N}^n} s_{ij_0}\left(\frac{\frac{N_{ijf}}{M_j}}{\frac{N_{ij_0}}{M_{j_0}}}\right)}_{\text{industry intensity effect new firms}} - \underbrace{\sum_j\sum_{f\in\mathcal{N}^o} s_{ij_0}\left(\frac{\frac{N_{ijf_0}}{M_{j_0}}}{\frac{N_{ij_0}}{M_{j_0}}}\right)}_{\text{industry intensity effect old firms}}$$

$$= \underbrace{\sum_j\sum_{f\in\mathcal{N}^p} s_{ijf_0}\cdot\%\Delta\left(\frac{N_{ijf}}{M_{jf}}\right)}_{\text{permanent firm intensity effect}}$$

$$\underbrace{+\sum_{t=1}^{T}\sum_j\sum_{f\in\mathcal{N}_t^n}\left(\frac{N_{ij_t}}{N_{i_0}}\right)\left(\frac{M_{jf_t}}{M_{j_t}}\right)\left(\frac{\frac{N_{ijf_t}}{M_{jf_t}}-\frac{N_{ij_t}}{M_{j_t}}}{\frac{N_{ij_t}}{M_{j_t}}}\right) - \sum_{t=0}^{T-1}\sum_j\sum_{f\in\mathcal{N}_t^o}\left(\frac{N_{ij_t}}{N_{i_0}}\right)\left(\frac{M_{jf_t}}{M_{j_t}}\right)\left(\frac{\frac{N_{ijf_t}}{M_{jf_t}}-\frac{N_{ij_t}}{M_{j_t}}}{\frac{N_{ij_t}}{M_{j_t}}}\right)}_{\text{net new firm entry intensity}}$$

$$\underbrace{+\sum_{t=1}^{T}\sum_j\sum_{f\in\mathcal{N}_t^n}\left(\frac{N_{ijf_t}}{N_{i_0}}\right)\%\Delta_t^T\left(\frac{N_{ijf_t}}{M_{jf_t}}\right)+\sum_{t=0}^{T-1}\sum_j\sum_{f\in\mathcal{N}_t^o}\left(\frac{N_{ijf_0}}{N_{i_0}}\right)\%\Delta_0^t\left(\frac{N_{ijf_t}}{M_{jf_t}}\right) +\frac{1}{2}\left(\sum_{t=1}^{T}\sum_j\sum_{f\in\mathcal{N}_t^n}\frac{N_{ijf_t}}{N_{i_0}}\%\Delta_t^T M_{jf_t}\%\Delta_t^T\left(\frac{N_{ijf_t}}{M_{jf_t}}\right)+\sum_{t=0}^{T-1}\sum_j\sum_{f\in\mathcal{N}_t^o}\frac{N_{ijf_0}}{N_{i_0}}\%\Delta_0^t M_{jf_t}\%\Delta_0^t\left(\frac{N_{ijf_t}}{M_{jf_t}}\right)\right)}_{\text{net new firm growth intensity}}$$

$$\underbrace{+\sum_j\sum_{f\in\mathcal{N}^p} s_{ijf_0}\left(\frac{\frac{N_{ijf}}{M_{jf}}}{\frac{N_{ijf_0}}{M_{jf_0}}}\frac{(\frac{M_{jf}}{M_{jf_0}}-\frac{M_j}{M_{j_0}})}{\frac{M_j}{M_{j_0}}}\right)}_{\text{permanent firm bias term intensity}}$$

$$\underbrace{+\sum_{t=1}^{T}\sum_j\sum_{f\in\mathcal{N}_t^n}\left[\left(\frac{M_{jf_t}}{N_{i_0}}\right)\left(\frac{N_{ij_t}}{M_{j_t}}\right)+\left(\frac{\frac{N_{ijf}}{M_{jf}}+\frac{N_{ijf_t}}{M_{jf_t}}}{2N_{i_0}}\right)\left(M_{jf}-M_{jf_t}\right)-\left(\frac{N_{ijf}}{N_{i_0}}\right)\frac{M_j-M_{j_0}}{M_j}\right] -\sum_{t=0}^{T-1}\sum_j\sum_{f\in\mathcal{N}_t^o}\left[\left(\frac{M_{jf_t}}{N_{i_0}}\right)\left(\frac{N_{ij_t}}{M_{j_t}}\right)-\left(\frac{\frac{N_{ijf_t}}{M_{jf_t}}+\frac{N_{ijf_0}}{M_{jf_0}}}{2N_{i_0}}\right)\left(M_{jf_t}-M_{jf_0}\right)\right]}_{\text{net new firm bias term intensity}}$$

Note that all terms labeled "net new firm" consist of term(s) relating to new firms and term(s) relating to old firms.

Appendix C Construction of the Instrument

The supply-push component of immigrant inflows refers to the exogenous part of the actual inflow to a local labor market that is attributable to existing ethnic concentrations. The underlying idea is that immigrants tend to settle in those areas where other immigrants of the same country of origin or cultural background have already settled before (Bartel,

1989, Jaeger, 2007). Suppose ΔI_c is the net overall number of immigrants with nationality c entering Germany during a given period.[27] In the absence of any local labor demand shocks, these new immigrants are likely to distribute themselves across Germany according to the existing distribution of their fellow countrymen. Let λ_{cr} represent the share of all immigrants of nationality c in Germany that reside in labor market r in some initial period and let θ_{ci} be the nationwide fraction of the newly arriving immigrants of nationality c that fall into skill group i. Then the number of new immigrants of nationality c with skill i that is expected to move to labor market region r is given by $\lambda_{cr} \times \theta_{ci} \times \Delta I_c$. Summing across source countries then gives an estimate of the expected overall skill-specific immigrant inflow into local labor market r:

$$SP_{ir} = \sum_c \lambda_{cr} \theta_{ci} \Delta I_c.$$

This supply-push component of recent immigration will be exogenous as long as λ_{cr} is uncorrelated with local demand shocks. Since older immigrant cohorts already living in Germany are also likely to relocate to labor market r in the presence of positive economic shocks, contemporary λ_{cr} will violate this condition. For that reason we use past immigrant distributions, using a lag of 10 years.[28] So for the period 1985 to 1995 we use the existing distributions in 1975. To normalize, we divide SP_{ir} by the overall skill-specific labor force in region r at the beginning of the immigration period. The supply-push rate we use as our instrument is then given by:

$$SPR_{ir} = \frac{\sum_c \lambda_{cr} \theta_{ci} \Delta I_c}{L_{ir_0}}.$$

In contrast to previous studies that have used the overall lagged foreign immigrant concentration as an instrument for current changes (for instance, Altonji and Card, 1991;

[27] In the IAB data we only observe an individual's nationality, not the country of birth. This means that some foreign nationals we observe in the data are actually born in Germany but have kept their parents' nationality. According to figures from the German Statistical Office, the share of second generation immigrants in the immigrant working-age population in 1995 is around 10%.

[28] It is generally advisable to go back as far as possible in time for the construction of the initial nationality shares to ensure that even serially correlated shocks have ceased to exert an influence. The only data available that allow a construction of nationality-specific immigrant shares across local labor markets in Germany are the IAB data, and these start in 1975.

Dustmann et al., 2005), we distinguish between fifteen nationality-specific immigrant distributions in Germany when constructing our instrumental variable. This is particularly important when analyzing a period during which the country of origin composition of immigrant inflows has changed significantly relative to the existing immigrant stock. For a new immigrant from Asia or Yugoslavia, the two largest groups of recent immigrants to Germany, the existence of a large, say Turkish community, the largest existing immigrant group in Germany in 1985, is presumably irrelevant for his or her location decision.