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ABSTRACT

In this paper, we empirically assess the causal links between trade and individual income risk and study the role that human capital plays in this relationship using a rich, worker-level, longitudinal data set from Germany spanning 1976 to 2012. Our estimates suggest substantial heterogeneity in labor income risk across workers in different entry cohorts and across workers with different levels of industry-and occupation-specific human capital. Our findings suggest that within-industry changes in imports and exports are causally related to income risk: Imports increase risk and exports decrease risk, and they do so in an economically significant manner. Importantly, we find there to be a complex interplay between human capital and the linkage between trade and risk: While, on average, individuals with higher levels of industry- or occupation-specific human capital experience lower income risk, a given increase in net-imports exposure in an industry increases risk for workers with higher levels of industry tenure more than it does for workers with lower levels of industry tenure. High levels of industry-specific human capital can be costly for workers in highly trade-exposed industries. By contrast, we find no evidence of any interaction between risk, industry trade exposure, and occupation-specific human capital.

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1 Introduction

The world economy has experienced remarkable growth in international trade in recent decades. Despite the economic gains that have consequently been achieved in the aggregate, there has been growing public apprehension regarding globalization. Of particular concern has been the effect of international trade on labor markets and, specifically, the fear that greater trade exposes workers to more volatile economic environments in which they face a higher risk of job displacement and income losses. Such effects may be heterogeneous across workers with different levels and types of human capital. For instance, as patterns of comparative advantage change over time leading to contraction of some industries and firms (and expansion of others), workers with experience narrowly relevant to their industry of employment face the risk that, if displaced, they may be unable to find employment elsewhere that suitably rewards their cumulative industry experience, while other workers, with more general experience (or skill sets), may do better (or possibly worse) in securing market returns for their experience. In turn, such uncertainty can impact the incentives for human capital accumulation with important implications for aggregate economic growth in the long term.[1]

Whether labor income risk (defined as the variance of unpredictable changes in earnings) indeed rises with trade exposure and whether trade affects different types of workers, with different human capital, differently are the core questions that motivate this paper. The economics literature has offered a variety of specific conjectures as to why individual income risk might be causally linked to trade, about how income risk, in general, could be related to human capital, and, finally, about how the nature of a worker's human capital could be relevant for the extent to which trade affects the income risk faced by workers. On the link between trade and risk, it has been variously argued that greater trade openness would expose an economy to more intense competition in product markets and greater variability in employment and wage outcomes.[2] Further, it has been conjectured that in settings with heterogeneous workers and firms, displacement of workers caused by trade could result in heterogeneous outcomes for similar workers and thus imply ex-ante risk (Helpman et al., 2010; Senses and Kurz, 2016). On the other hand, trade integration in goods markets with the rest of the world could serve to stabilize prices and labor market outcomes in volatile

[1] Using an incomplete-markets version of an endogenous growth model calibrated to US data, Krebs (2003) has argued that the theoretical elimination of idiosyncratic risk to labor income can lower economic growth rates by up to 0.5 percentage points. Wasmer (2006) has argued, theoretically, that lower employment protection can, on the margin, lower the incentives for workers to acquire specific skills (relative to general skills), with potential implications for firm-level and aggregate productivity.

[2] More specifically, Rodrik (1997) has argued that the greater elasticity of demand in product markets following trade openness will result in greater elasticity of demand in factor (labor) markets, thus resulting in greater variability in employment and wages following exogenous productivity shocks. This theoretical proposition has been variously quantitatively evaluated by Slaughter (2001), Krishna et al. (2001), Senses (2010), and Hijzen and Swaim (2010), among others. See also Giovanni and Levchenko (2009), for interesting cross-country evidence regarding the links between trade and sectoral output volatility and Cosar et al. (2016) for a dynamic analysis of the effects of globalization on firm level volatility and wage inequality in Colombia.

economies. Diversification of demand shocks across multiple destinations, could similarly imply lower volatility in exporting sectors, with lower likelihood of displacement and more uniform outcomes across workers (lower risk). The sign of the relationship between risk and trade (imports and exports) is thus theoretically ambiguous and needs to be empirically determined.

How would human capital matter for risk? Even in closed-economy settings, a variety of economic shocks can have heterogeneous impacts on workers based on their characteristics. For instance, a given cohort of workers may be subject to greater variation in initial year earnings and in income growth based on the economic environment in the cohort's year of entry into the labor market. Further, with age, workers may become better (or possibly worse) at navigating labor market shocks, following such events as involuntary job loss and unemployment, thus leading to more heterogeneous outcomes across cohorts. Importantly, workers with different human capital may be affected differently by economic shocks. For instance, those with more general skill sets and experience that enable them to be similarly productive in a range of different jobs, occupations, and industries will likely be able to weather economic shocks better than workers with more specific forms of human capital, which make them better (or only) suited to particular industries or occupations.[3]

In the specific context of international trade, changes in trade outcomes in a given industry (due to changes in trade policy or in the patterns of comparative advantage, for instance) are likely to affect workers with high levels of industry-specific human capital differently than workers in the same industry with high levels of occupation-specific human capital or workers in the industry with more general human capital. Specifically, we can conjecture that with a surge in imports and the consequent reallocation of workers across firms and industries, workers with mostly general human capital will easily move between jobs, possibly switching industries and firms with limited impact on their income, and as a result, experience low levels of income volatility, while those with more industry-specific forms of human capital may face more heterogeneous outcomes and thus, greater risk.

Whether greater trade exposure will indeed increase individual income risk and whether the nature and extent of worker human capital plays a quantitatively significant role in this relationship are both questions whose answers can only be determined through detailed empirical analysis. In this paper, we undertake just such an analysis of the association between trade, human capital, and labor income risk in Germany using longitudinal worker-level data from the Institute for Employment Research spanning from 1976 to 2012. To get to each of the economic linkages we have highlighted above, we proceed in multiple steps. First, we estimate time-varying labor income risk parameters for workers employed in

[3]Important earlier analyses, focusing on human capital specificity and labor market outcomes in domestic settings, include Neal (1995) and Parent (2000) on the role of industry-specific human capital, Kambourov and Manovskii (2009) on occupation-specific human capital and, Gathmann and Schönberg (2010) on task-specific human capital. See also Artuc et al. (2010), Dix-Carneiro (2014) and Dix-Carneiro and Kovak (2017) which have variously analyzed the issue of labor mobility, across physical and economic space with heterogeneous workers.

different industries. We adopt specifications of the labor income process which distinguish between transitory and persistent shocks to labor income – an important distinction as the former can be smoothed using self-insurance, while the latter cannot, and will thus have greater welfare consequences. The longitudinal richness of our data allows us to address a variety of issues that have challenged earlier studies on income risk. Specifically, given that labor income risk varies with age (Feigenbaum and Li, 2012) and that different cohorts of workers may experience different entry-year effects (Altonji et al., 2016; Kahn, 2010), the heterogeneity in the composition of the workforce across sectors and over time can be crucial. We account for this by estimating time-varying income risk parameters separately for different entry cohorts in different industries. We find strong evidence of cohort effects, with different cohorts experiencing quite different levels of risk in their initial years in the labor market. Further, consistent with earlier findings, we find that income risk is non-monotonically related to age: Risk generally declines with age and then rises slightly towards final career stages. These factors, taken together, underscore the need for the cohort-level approach we undertake to estimating risk.

In the next stage of our analysis, we use our industry-level time-varying estimates of the persistent component of labor income risk to study the causal links between trade and labor income risk. The German economy provides an excellent context to study this relationship for a couple of reasons. Germany is a large trading nation with a range of diversified exports to and imports from its partner countries, which allows for the exploitation of substantial industry-level variation in trade outcomes. Further, as in Dauth et al. (2014), we focus on Germany's trade with China and Eastern Europe, both of which increased substantially during our sample period for plausibly exogenous reasons – China's entry into the WTO in 2000 and the fall of the "Iron Curtain" in Eastern Europe in the early 1990s. To further address the potential endogeneity concern that trade outcomes themselves may be driven by domestic German factors that also determine income risk experienced by German workers, we use an instrumental variables approach. Our empirical results for Germany suggest that within-industry changes in imports and exports (per worker) are strongly and causally related to income risk. Imports increase risk and exports decrease risk in an economically significant manner. For instance, the mean increase in industry imports per worker between 2000 and 2007 results in a 9 percent increase in income risk, while the mean increase in industry exports per worker in the same period results in a 7 percent reduction in income risk.

The final stage of our analysis concerns the role of human capital in the trade-risk relationship and is the primary focus of this paper. Due to availability of extremely detailed information on workers' labor market biographies in our dataset, we are able to construct various measures of skill specificity such as industry and occupation tenure, and occupational centrality.[4] We then estimate industry-specific income risk parameters for workers

[4]Industry and occupation tenure are measured as the number of quarters of accumulated work experience in the worker's current industry and occupation, respectively. Occupational centrality is a measure of transferability of skills, with more central workers as defined as those who have acquired experience in tasks

that vary over time and with the level of industry- and occupation-specific human capital, and document substantial variation in risk across different worker types and over time. Our estimates indicate that income risk is negatively related to both industry tenure and occupational tenure, as well as individual occupational centrality. This suggests that, in general, higher levels of both specific human capital and transferability of skills across occupations help individuals better manage the consequences of economic shocks. Importantly, we find a significant and complex interplay between human capital and the causal linkage between trade and risk. The increase in risk caused by a given increase in net imports in an industry is systematically higher for workers with higher levels of industry specific human capital in that industry. While high levels of industry-specific human capital lower risk in general, this is not the case for workers in highly trade-exposed industries: We find that in industries with high net imports, workers with the highest levels of industry tenure face higher risk overall than workers with lower levels of industry tenure.

Moreover, we also find that while net import exposure at the industry level raises the level of risk experienced by workers, this effect is independent of the level of occupational tenure. Our results, therefore, suggest that the role played by specific human capital in determining the causal association between trade exposure and income risk crucially depends on the nature of specificity of the human capital of workers. Since trade "shocks" are industry "shocks" to first order, they affect differentially those with high levels of industry tenure relative to those with low levels of industry tenure, but appear to have a relatively homogeneous effect on those, *ceteris paribus*, with different levels of occupation tenure.

This paper engages several important and interrelated strands of the economics literature. First, it contributes centrally to a very substantial debate concerning the labor market effects of international trade. Much of this discussion has concerned the impact of trade on the (mean) level of earnings or employment.[5] By contrast, this paper explores the causal impact of trade on labor income volatility, along the lines of earlier work by Krebs et al. (2010) and Krishna and Senses (2014).[6] It is the first paper to focus on the role of human capital in determining the link between trade and individual income risk. Our finding that higher levels of human capital may act to the detriment of workers in highly trade-exposed

similar to those utilized in high-employment share occupations in the economy. These measures are described in detail in the next section.

[5]A large literature has examined the effects of trade openness on mean wage levels of workers with different levels of skill. Goldberg and Pavcnik (2007) and Feenstra and Hanson (1999), among others, provide comprehensive surveys of this literature. A more recent literature focuses on the mean wage impact of trade on workers employed in different industries or in different localities, in the context of the China shock. See for example, Autor et al. (2013), Dauth et al. (2014, 2021) and Pierce and Schott (2016).

[6]The positive association between imports and risk we document for Germany is consistent with earlier findings for Mexico (Krebs et al., 2010) and for the US (Krishna and Senses, 2014). By contrast with these earlier papers which use longitudinal panels with limited time dimension, we use full employment histories of workers in this study, allowing us to obtain more precise estimates of individual income risk that vary across workers in different entry cohorts, with different levels and types of human capital. Importantly, the identification methodology used in the present study also allows us to make a stronger causal claim than these earlier studies.

industries stands in sharp contrast with common perceptions concerning the more adverse impact of trade on workers with lower human capital and underscores the need for more elaborate considerations of human capital and of income volatility in the understanding the consequences of international trade on labor markets.

Second, the extraordinarily rich worker-level dataset used in this paper allows us to contribute to the literature on individual income volatility[7] and to improve on earlier work in at least two important dimensions. First, the long time span of the data implies that we are able to achieve a more precise separation between transitory and persistent shocks to income for a much larger sample of workers than has been generally possible. Second, the large sample size and the unique cohort structure of our data allow us to estimate heterogeneous age-risk profiles and labor market entry-year effects for workers in different cohorts and in different human capital groupings separately, helping to better understand the dynamic evolution of income risk for heterogeneous workers.[8] As we will discuss, recognizing these heterogeneities and accounting for them is important in assessing the role of human capital in the links between trade exposure and risk.

Finally, the findings of this paper concerning the risk-related costs of industry-specific human capital in an open economy informs, both quantitatively and qualitatively, a broader debate concerning the longer term costs and benefits of globalization with respect to implications of openness for endogenous human capital choices and, in turn, for aggregate economic growth. If acquiring human capital is costly, individuals, on the margin, will acquire less of it, with negative implications for long-term growth and with associated welfare costs (as in Krebs (2003)). Equally, the choice of certain forms of human capital relative to others (i.e., specific relative to general human capital) will have implications for the nature of the aggregate human capital stock of an economy, with its own associated costs and benefits. While the present paper is silent on the question of endogenous human capital choice in the presence of income risk, a detailed quantitative consideration of that question is an important topic for future research.

The rest of the paper proceeds as follows. In Section 2, we describe the worker-level data and the construction of main human-capital measures. In Section 3, we provide details of the estimation of income risk and investigate the properties of our risk estimates in relation to human capital. In Section 4, we study the causal impact of trade on income risk. In Section 5, we put human capital back into play and highlight its role in the effects of trade on risk. Concluding remarks are offered in the last section.

[7] See for example, Gottschalk and Moffitt (1994), Carroll and Samwick (1997), Meghir and Pistaferri (2004), Hryshko (2012), Carey and Shore (2013), among others.

[8] By comparison, for the United States, the well-known Population Study of Income Dynamics (PSID) while similar along the longitudinal dimension, covers a much smaller sample of workers, making it all but impossible to study cross-industry effects of the type we are interested in exploring here.

2 Worker-Level Data

This paper empirically assesses the relationship between trade, individual income risk, and human capital using worker-level data from Germany. The estimation of individual income risk parameters that vary over time and across industries with different exposure to trade requires longitudinal data on a large number of workers over a long duration. Moreover, workers need to be observed from their years of entry into the labor market in order to allow for cohort effects and to appropriately calculate the human capital they have acquired throughout their labor market experience. In our analysis, we use data from the Institute for Employment Research (IAB) over the 1976-2012 period, which provides complete employment histories of on average around 75% of the labor force in various entry cohorts, with over a million workers in each cohort. In this section, we discuss in detail the structure of our dataset and the construction of the various measures of human capital that we employ in our analysis.

From the Employment History (BEH) data provided by the IAB, we draw entire employment histories for the workers who entered the labor market in "even" calendar years between 1976 and 2006. For the sixteen even-year entry cohorts during this period, we have detailed data on personal characteristics (e.g., gender, education level, nationality) and job characteristics (e.g., occupation, wage, industry, location) for each job that each worker has held since their entry into labor market, until 2012. We restrict our sample to include only West German workers because the workers in the former East German regions appeared in IAB only after the reunification, which makes it impossible to track their labor market histories and acquisition of human capital prior to the reunification. We also omit new entrants to the East German labor market which is structurally very different from that of West Germany, especially during the years of economic transition. Our current analysis is restricted to men, as women differ in terms of their labor market attachment, hours worked and human capital acquisition decisions. To ensure that we capture the first-time labor market entrants for each entry cohort, we impose education-qualification-specific age limits on workers when they were first observed in our sample.[9] Following Krishna and Senses (2014), for the purpose of risk estimation, we further exclude workers whose quarterly earning in any quarter was ever below 5% or above 200% of his own career mean. After these restrictions, the resulting sample contains about 120,000 manufacturing workers for each entry cohort.

We estimate income risk over five non-overlapping panels, each spanning six years and organized at the quarterly frequency: 1983-88, 1989-94, 1995-2000, 2001-06, and 2007-12. Each panel includes working-age men who have entered the labor market prior to the beginning of the panel. For instance, the 1983-88 panel consists of all workers who entered the labor

[9] More specifically, we record the age when a worker is first observed in the dataset, and we exclude this worker from the sample if his age is above 21 for a middle school diploma holder or below, above 23 for a vocational training diploma holder, above 24 for a high school diploma holder, above 26 for a high school diploma holder with vocational training, and above 28 for a technical college degree holder.

market before 1983 (in 1976, 1978, 1980, and 1982), while the 2007-12 panel consists of all workers who entered the labor market between 1976 and 2006 (16 entry cohorts in total). For our analysis, we restrict the sample to workers employed in the manufacturing sector as of the first quarter of each panel, who may or may not have stayed in that sector in the years that follow. The first and second columns of Table 1 report the number of entry cohorts included in each panel along with the total number of workers as of the first quarter of each panel. By construction, the sample size increases with each consecutive panel, from about half a million workers in the first panel to over a million in the last panel.

Due to the structure of our dataset, earlier panels consist mainly of younger workers with fewer years of experience. For instance, the 1983-88 panel includes men with a maximum labor market experience of 6 years (24 quarters) at the beginning of the panel, while the 2007-12 panel includes workers who entered the labor market 30 years prior to the beginning of the panel, as well as workers who entered only one year prior, in 2006. This feature of the data is reflected in an increase of both the mean and standard deviation of experience (measured as the cumulative quarters of employment) with each consecutive panel.

Specific Human Capital

The extent and nature of human capital possessed by workers are central to our analysis. Workers with different types and levels of human capital will be exposed to different levels of risk for a number of reasons. First, they may experience a differential probability of displacement from their jobs. This would be the case if for example, firms are more reluctant to let go workers who have invested in more specific human capital. Second, the extent to which displacement will affect different workers depends on the ease with which they can transition to new jobs. This itself is a function of their human capital and may depend, in particular, on the skills that they have acquired over their careers and how transferable those skills are to other jobs.[10] For instance, workers with high levels of industry-specific human capital may face greater risk following an industry-level shock (e.g. trade shock), since such a shock will likely yield a larger dispersion in wage outcomes among workers who kept their jobs and those who were forced to leave their industry and thus, lose the returns to their specific human capital following the shock. Such wage dispersion among otherwise similar workers with low levels of specific human capital is likely to be lower.

To explore the extent to which such specificity of human capital may matter for risk, we construct two measures of specific human capital. Industry tenure is calculated as the cumulative quarters of employment in the industry in which the worker is employed, measured

[10]Following displacement, workers who switch industries (Neal, 1995; Parent, 2000) or occupations (Kambourov and Manovskii, 2009), and those who move to more distant occupations in terms of task requirements (Gathmann and Schönberg, 2010) experience larger wage losses compared to those who do not experience such switches that result in loss of (industry- or occupation- or task-) specific human capital. Relatedly, Utar (2018) and Dauth et al. (2021) find job transitions following an import shock, to be more difficult for workers in occupations utilized in smaller number of industries.

as of the first quarter of each panel. Similarly, occupational tenure is the cumulative quarters of employment in the same occupation as of the beginning of each panel. Industries are classified at the 3-digit level (NACE Rev.1) for 92 manufacturing industries, and occupations are classified at the 2-digit level (KldB 1988) aggregated to 37 occupations. The fifth and sixth columns of Table 1 summarize industry and occupational tenure. The two measures of specific human capital are comparable to each other and on average lower than total experience due to workers switching occupations and industries.

Occupational Centrality

Workers can respond to an adverse labor market shock by switching occupations. While some of the occupation-specific human capital accumulated by a worker will be lost following such a switch, the worker may be able to transfer some of his skills from his old occupation(s) to his new occupation. The transferability of the skills that the worker has acquired throughout their years of employment will determine the ease with which the worker can switch in and out of occupations, the wage consequences of such a switch,[11] and, hence, the income risk that the workers face. To get at this idea, we construct an occupational centrality measure for each worker. More central workers are defined as those who have acquired experience in tasks similar to those utilized in high-employment-share occupations in the economy.

To measure occupational centrality for individual workers, we take the following steps.[12] First, we construct an occupation-level task vector, which summarizes the task requirements of a given occupation. We create and use two measures of this vector. The first measure is directly obtained from the Berufenet database, which is based on expert knowledge about the job requirements of each occupation in Germany (Dengler et al., 2014). Each occupation in this database is described by a 5-dimensional task vector. The second is constructed from the BIBB Surveys of the Working Population on Qualifications and Working Conditions in Germany (Rohrbach-Schmidt and Tiemann, 2013). For our baseline results, we use the 1999 wave of the survey of around 35,000 workers on the type and intensity of tasks they complete in their jobs, which we use to construct a 13-dimensional task vector for each occupation.

Next, we calculate a cumulative task vector for each worker, which records, for each quarter in each year, the experience a worker has accumulated in different job tasks. This exercise tracks a worker's employment duration in each occupation since the worker's year of entry to the labor market, along with the occupational task vector for each of these occupations. Finally, we calculate the similarity (angular separation measure) between the cumulative task vector of the worker and each occupation in the entire economy. Occupation centrality of the worker is then the average similarity between his task vector and all the

[11] Gathmann and Schönberg (2010) construct a task-specific human capital measure to analyze portability of skills accumulated in the labor market. Their results suggest that wage losses following displacement, on average, are higher in occupations with skill requirements that are very different from other occupations, and lower if individuals are able to find employment in an occupation with similar skill requirements.

[12] Please see Appendix A.1 for a detailed description of the construction of the centrality measures.

occupations, weighted by the economy-wide employment share for each occupation.[13] The less distant the two vectors are, the easier it is for the worker to switch to an occupation that requires tasks in which she has the experience and hence will be able to transfer some of their accumulated human capital to the new job.[14] In our sample, the average centrality is relatively stable across panels, with a mean around 0.6 for the Berufenet measure and a mean of 0.8 for the BIBB measure.

3 Estimation of Income Risk

The first step of our empirical analysis is the estimation of time-varying income risk for workers employed in different industries. In this section, we describe in detail the estimation of income risk and emphasize the importance of allowing for heterogeneous risk profiles that evolve over workers' lifetime. Specifically, we allow for industry level income risk to systematically vary by entry cohort and the level of human capital the workers have acquired throughout their labor market experience and document this variation as a consistent feature of the data.

For notational simplicity, we start by outlining a general approach to estimating income risk using longitudinal data on individual income for workers employed in a given industry, abstracting away from any other source of variation in risk (e.g. across panels, entry cohorts, or levels of human capital). We assume that the log of quarterly labor income of individual i in quarter t employed in industry j is given by:

$$\log(y_{ijt}) = \alpha_j + \alpha_r + \alpha_o + \alpha_t + \beta_j x_{ijt} + u_{ijt}, \tag{1}$$

where labor income is defined as the quarterly sum of earnings from both full-time and part-time ordinary jobs (as opposed to mini-jobs which are considered as marginal employment);[15] α_j, α_r, α_o, and α_t denote the industry, region, occupation, and time (year-quarter) fixed effects respectively, with industry, region, and occupation of an individual identified as of the first

[13]The similarity measure we use is akin to the distance measure in Gathmann and Schönberg (2010) constructed to estimate the similarity of different occupations in the economy. The measure we use differs as it is worker-specific, and measures the distance of the individual workers' accumulated task vector from each occupation in the economy.

[14]The angular separation measure treats each task symmetrically in terms of how similar various tasks are. But in practice, a task like "research and development" is likely a much more similar to "gathering information, investigating and documenting" compared to a task like "taking care, healing". A more aggregate task vector such as the one from the Berufenet database is less subject to this problem. This advantage comes at the expense of a more accurate description of the tasks completed in a given occupation that a more detailed task vector like the one constructed using the BIBB survey affords. Thus, we use both measures of centrality in our analysis. We have also conducted various robustness checks such as allowing for time-varying task requirements using consecutive waves of the BIBB surveys (in years 1986, 1992, 2006) and using employment shares in a given district ("kreis") rather than economy-wide employment shares, as weights. We find various versions of these measures to be highly correlated with each other. For details, see Appendix A.1.

[15]In the case of an individual holding multiple ordinary jobs during the same time period in the original spell-level data, we only consider income from the highest-paying ordinary job. We exclude from our sample those workers who held more than two ordinary jobs at any point in their employment history.

quarter of the panel; β_j denotes industry-specific returns to (time-varying) observable worker characteristics represented by x_{ijt}.

We consider two different versions of (1) depending on the individual-level observables included in x_{ijt}. In the baseline specification, we include in x_{ijt} only the age, the square of age, and dummy variables representing the beginning-of-panel education level.[16] We also consider an alternative specification, which includes a much wider range of determinants of wages which are constructed from the workers' detailed employment histories. These variables include proxies for general human capital (experience, experience-squared, and task-experience-based centrality) and various measures of specific human capital (occupational tenure, industry tenure, firm tenure, and task tenure) the worker has acquired in the labor market.[17] All human capital measures are calculated as of the beginning of each panel. We note here that the inclusion of detailed individual characteristics such as occupation-, industry-, firm-specific, and task-based human capital as well as the individual's centrality is only possible due to the highly detailed employment biographies of the workers that are available through our dataset. This exercise constitutes, in itself, a modest data-driven innovation to the literature on wage determination. Table A1 reports the estimation coefficients over the entire sample by pooling all the panels together, for the baseline Mincer specification in Column (1) and the detailed Mincer specification in Column (2). We find wages to increase with experience (at a decreasing rate) and education, as well as with various forms of specific human capital, measured as firm-, industry-, occupation- and task-tenure. We find workers with higher occupational centrality, on average, to have lower wages.[18]

In (1), the residual, u_{ijt}, is the stochastic component, which represents variation in individual income that cannot be explained by variation in returns to observable worker characteristics included in x_{ijt}. The conceptual distinction between the two versions of the Mincer specification is what we assume are changes in wages that are unpredictable from the worker's perspective (hence, part of risk). In the benchmark, more parsimonious setting, the only individual-specific characteristics workers condition on to forecast the future earnings trajectory are age and education level. This is a relatively conservative way to model the forecasting rule. In the extended setting, we assume that workers are sophisticated enough to understand the role of various forms of human capital and condition their forecasts on a wide array of human capital measures. As all the human capital measures are calculated as of the beginning of each panel, the possibility of unemployment in the future and the likelihood of

[16]The education variable is an indicator variable for six categories: middle school diploma or below, vocational training degree, high school diploma, high school diploma with vocational training, technical college degree, and university degree. Missing values are imputed as in Fitzenberger et al. (2006).

[17]Firm tenure is calculated as the cumulative quarters of employment in the same firm as of the beginning of each panel. Task tenure is constructed as in Gathmann and Schönberg (2010). At the beginning of each panel, we project the cumulative task-specific experience the worker possesses to the task requirement of the worker's current occupation. Please see Appendix A.1 for the construction details of task tenure.

[18]While for exposition and brevity, we report in Table A1 the estimated coefficients from a Mincer regression which pools workers in all panels, in our benchmark risk estimates we in fact estimate (1), separately by panel, and depending on the specification, also by industry and cohort.

job switches across industries, firms, and occupations, as well as any variation in returns to time-varying worker characteristics over their average, are considered unpredictable and part of the income risk.

The residual u_{ijt} itself is assumed to be the sum of two unobservable components, a persistent component ω_{ijt} and a transitory component η_{ijt} which itself can be decomposed into moving average terms:

$$u_{ijt} = \omega_{ijt} + \eta_{ijt} = \omega_{ijt} + \sum_{k=0}^{K} \theta_{ijt-k}, \tag{2}$$

where the persistent component ω_{ijt} follows a random walk so that these shocks to income are fully permanent:

$$\omega_{ijt+1} = \omega_{ijt} + \varepsilon_{ijt+1}, \tag{3}$$

The innovation terms ε_{ijt} and θ_{ijt} are distributed independently over time and identically across individuals in the same industry, with $\varepsilon_{ijt} \sim N(0, \sigma^2_{\varepsilon j})$ and $\theta_{ijt} \sim N(0, \sigma^2_{\theta j})$, respectively. The variance terms $\sigma^2_{\varepsilon j}$ and $\sigma^2_{\theta j}$ then measure the magnitude of permanent and transitory income risk in industry j over the duration of a given panel. The moving average terms in (2) are included to filter out medium-run shocks – transitory income shocks that last longer than one period but are not permanent and will dissipate after K periods (as in Meghir and Pistaferri (2004)). In our benchmark specification, we allow for transitory shocks that last up to two years (denoted by $K = 2$ years) but also consider alternative specifications of the labor income process in which transitory shocks last up to a year ($K = 1$ year) or up to three years ($K = 3$ years).

Under this income specification, the cross-sectional variance in residual income changes across individuals subject to the same shock over an n-period time difference ($n > K$) can be written as in Carroll and Samwick (1997):

$$Var(\Delta_n u_{ijt}) = 2\sigma^2_{\eta j} + n\sigma^2_{\varepsilon j}, \tag{4}$$

where $\sigma^2_{\eta j} = (K+1)\sigma^2_{\theta j}$. Thus, the permanent income risk parameter $\sigma^2_{\varepsilon j}$ is simply estimated as the slope of the linear relationship between the cross-sectional variance of residual income changes and the time period over which this income difference is calculated. Identification comes from the fact that as we consider longer income differences, the transitory shocks disappear while the persistent shocks accumulate.

Our analysis mainly focuses on the permanent component of income risk due to its greater welfare significance. While workers, in general, can effectively self-insure against transitory shocks through borrowing or using their own savings, highly persistent income shocks have a substantial effect on the present value of future earnings and therefore lead to significant changes in consumption and welfare. Moreover, our methodology is so that the transitory component of risk is estimated with noise as it also absorbs any measurement error.

We estimate the permanent component of income risk at the industry level separately for the five consecutive and non-overlapping 6-year panels, assuming both transitory and permanent shocks to income have the same distribution during panel p, for workers employed in industry j as of the beginning of each panel ("Pooled Sample"). Next, we estimate the parameters characterizing income risk in each industry and panel separately for individuals in different entry cohorts ("Cohort Sample"). The cohort-level analysis of risk is motivated by two findings in the literature. First, income risk is documented to decline with age until, possibly, the final career stages (Feigenbaum and Li, 2012). Second, the year of entry in the job market affects both the initial level and dispersion of incomes across individuals (Kahn, 2010; Altonji et al., 2016). We test whether this type of systematic variation in risk is prevalent in the German labor market and, importantly, control for any such variation across entry cohorts in our analysis of the links between income risk and trade.

Finally, we allow for income risk to vary across workers who have acquired different levels of industry- and occupation-specific human capital. That is, we estimate risk for workers employed in industry j during panel p by quartiles of specific human capital measured by industry tenure or (alternately) occupational tenure. To calculate quartiles of human capital, we sort workers in a given panel (or in a given entry-cohort for cohort-level analysis) by their industry (or by their occupation) tenure.[19] This additional industry or occupation tenure dimension provides important variation in our context, as workers who have acquired different levels of specific human capital in an industry or occupation may differ in terms of their probability of displacement and their likelihood of experiencing an industry or occupational switch, as well as in terms of dispersion in wage outcomes following a trade shock.

Estimates of Income Risk

In Table 2, we provide a summary of our estimates of the permanent component of individual income risk, σ^2_ε for the pooled sample. Specifically, we report the mean and standard deviation of risk estimates across manufacturing industries computed for each panel. The permanent component of risk is estimated by filtering out transitory shocks with a duration of less than two years ($K = 2$) and, alternately, less than one year ($K = 1$). The mean estimate of risk during the years 1983-88 under $K = 2$ is 0.0033. This corresponds to a quarterly standard deviation of income growth of 0.057 and an annualized standard deviation of 0.115. The corresponding estimate for $K = 1$, where we filter out shocks of shorter duration, is, as expected, slightly higher, with $\sigma^2_\varepsilon = 0.0035$. The estimates in Table 2 suggest that mean income risk for the pooled sample decreases steadily for more recent panels, with estimates of risk about half of that of the initial panel (1983-88) during the last panel (in 2007-12), for both measures of risk.

[19]Alternatively, as we describe in the next section, for a given panel (and entry cohort), workers are sorted into four quartiles based on explicit tenure bins: Less than 2 years, between 2 and 5 years, between 5 and 10 years, and greater than 10 years.

While this reduction in risk could reflect an overall trend in the economy, it also may be due to the changing age composition of the worker sample across panels. As noted earlier, due to the cohort structure of our dataset, earlier panels consist of more significant proportions of younger workers. If risk systematically decreases over workers' lifetimes, the reduction in risk over time may simply be due to compositional differences across panels. To explore this possibility further, Table 3 provides summary statistics concerning the evolution of risk over time for selected cohorts in our sample. Consider first the 1976 entry cohort, which enters the labor market seven years prior to the 1983-1988 panel (the earliest panel we consider). This entry cohort has 18 years of potential experience by 1994, 24 years of potential experience by the year 2000, and so on until they reach 36 years of potential experience by 2012. For this cohort, risk declines steadily from 0.0020 in 1983-88 to 0.0011 during 2007-12, with the exception of a slight uptick during the 2001-06 panel. Similarly, consider the 1988 entry cohort, which has six years of potential experience by 1994 and 24 years of potential experience by 2012. The evolution of risk for this cohort over time suggests a monotonically declining evolution of risk with age.[20]

Table 3 also indicates substantial variation in income risk depending on the year of entry into the labor market.[21] The variation is especially large at early career stages, as is seen from the risk estimates in Table 3 for the cohort which enters the labor market one year prior to each panel (e.g., 1982 cohort in the 1983-1988 panel). Risk estimates vary considerably across different entry cohorts: risk at its lowest at 0.045 during 1989-94 for the 1988 cohort and at its highest at 0.0095 during 2001-06 for the 2000 cohort.[22]. The substantial heterogeneity in risk by entry cohort, along with the evolution of risk with age, validates an essential aspect of our empirical approach, which involves using longitudinal data to estimate risk separately for workers in different entry cohorts and, importantly, to incorporate these differences in our exploration of links between risk, human capital, and international trade.

Next, we explore any heterogeneity in the permanent component of risk across workers who enter the labor market in the same year but differ in terms of the type of human capital they have acquired after entry. Table 4 presents estimates from preliminary explorations of the association between risk and specific human capital. Columns (1) through (3) report estimates from specifications in which the dependent variable is income risk estimated separately for workers in each entry cohort, who are employed in a given industry as of the beginning of each panel and have acquired similar levels of industry-specific human capital so that they are in the same quartile of the industry-tenure distribution for that cohort. Each specification includes dummy variables for each industry tenure quartile, with the omitted category being

[20]Feigenbaum and Li (2012) document a similar variation of risk over the life cycle, with risk declining with age followed by a brief uptick for the oldest workers in the US.

[21]This finding is consistent with the large literature that document that the year of entry in the job market affects the initial level and dispersion of incomes of individuals in different cohorts (Kahn, 2010; Altonji et al., 2016; Schwandt and von Wachter, 2019).

[22]Incidentally, 2001-06 period coincides with a steady rise in youth unemployment rate in Germany, from 7.79% in 2001 to 15.53% at its peak in 2005 (World Bank, 2021).

the lowest quartile of industry tenure, as well as panel, industry, and cohort fixed effects. The estimates indicate that risk is systematically negatively associated with industry tenure: In Column (1), the coefficients on the dummy variables for industry tenure quartiles are all negative and monotonically increasing (in absolute value) for higher tenure quartiles. The risk for workers in the second quartile of industry tenure is 49 percent of the risk of workers in the lowest quartile (the omitted category). The risk for workers in the third quartile is even lower (40 percent) and is the lowest for workers in the fourth quartile (33 percent). Note that the inclusion of cohort fixed effects in the specification implies that we are identifying this correlation between risk and industry tenure by exploring the variation in risk across workers with similar levels of potential experience but who differ in terms of industry-specific human capital that they have acquired. Columns (2) and (3) include additionally on the right-hand side the average levels of the two centrality measures for the same group of workers. Both measures are negatively related to risk, i.e., the risk is lower for workers who have acquired experience in tasks that are similar to those required by the (employment-weighted) occupations in the economy ("central" workers). Importantly, the inclusion of centrality measures does not alter the coefficients on the industry tenure quartile dummies, which remain quantitatively similar to the coefficients reported in Column (1) and also remain statistically significant.

Columns (4) through (6) report estimates from analogous specifications with quartiles of occupational tenure instead of those of industry tenure. Again, risk is systematically negatively related to occupational tenure. The coefficients on all the occupational tenure quartile dummies are negative and consistently higher (in absolute value) for workers in higher quartiles of the occupational tenure distribution: the second quartile experiences risk that is 55 percent that of the risk experienced by workers in the lowest occupational quartile, and the third and fourth quartiles experience risk that are 47 percent and 37 percent of the risk in the lowest quartile. Centrality measures, included in Columns (5) and (6), remain negatively related to risk, and their inclusion does not alter the estimated association of risk with occupational tenure.

Overall, then, our risk estimates indicate substantial heterogeneity in risk across cohorts and over time. Income risk is systematically negatively related to industry and occupational tenure as it is to centrality: both specific human capital and transferability of skills across occupations are negatively related to risk. While these estimates present a broad characterization of the links between human capital and risk, they do not inform us of the extent to which trade exposure may affect risk for workers with different levels (and forms) of human capital. It is this interplay between risk, human capital, and trade exposure, which we proceed to explore causally while exploiting the cross-sectional and time-series variation in risk parameters that we have estimated.

4 Trade and Income Risk

To empirically assess the direction and magnitude of any causal association between income risk and trade, we regress time-varying industry-level income risk estimates from the last section, on the corresponding imports-per-worker (Imp) and exports-per-worker (Exp), in specifications that include an array of fixed effects and industry-specific time trends. In our benchmark specification, the dependent variable, $\sigma^2_{\varepsilon jp}$, is the estimated permanent component of risk for workers employed in industry j as of the first quarter of panel p:

$$\log \sigma^2_{\varepsilon jp} = \gamma_p + \gamma_j + \delta_j p + \beta Z_{jp} + \gamma_M Imp_{jp} + \gamma_X Exp_{jp} + \nu_{jp}. \tag{5}$$

Industry fixed effects, γ_j, are included to control for any time-invariant industry-specific factors that may be correlated with income risk and panel fixed effects, γ_p, are included to control for any changes in macroeconomic conditions that affect the level of income risk across all industries within a panel. $\delta_j p$ captures any industry-specific time trends. Z_{jp} are additional time-varying industry-level controls including the share of workers in six main education categories and the share of foreign-born workers. Equation (5) is estimated for the "pooled sample", for which industry-level risk for each panel is estimated by including all workers who entered the labor market before the beginning of that panel.

In an alternative specification, we allow income risk measures to vary by entry cohort ($\sigma^2_{\varepsilon jpc}$), and include in the regression cohort fixed effects (α_c) to account for any variation in the level of risk across workers who differ in terms of the time of entry and experience in the labor market:

$$\log \sigma^2_{\varepsilon jpc} = \gamma_p + \gamma_j + \gamma_c + \delta_j p + \beta Z_{jpc} + \gamma_M Imp_{jp} + \gamma_X Exp_{jp} + \nu_{jpc}. \tag{6}$$

In constructing imports and exports per worker, we follow Dauth et al. (2014) and focus on Germany's trade with China and Eastern Europe[23] in order to exploit plausibly exogenous variation in trade exposure vis-à-vis these countries:

$$Imp_{jp} = \frac{Imports_{jp}^{\text{Germany} \leftarrow \text{East}}}{Emp_{jp}} \quad \text{and} \quad Exp_{jp} = \frac{Exports_{jp}^{\text{Germany} \rightarrow \text{East}}}{Emp_{jp}},$$

where the numerators are the total imports from and total exports to China and Eastern Europe and Emp is the employment of industry j. In our benchmark specification, we calculate Imp_{jp} and Exp_{jp} over a given panel p and industry j as the 6-year annual average, but consider alternative measures in various robustness checks.

In Table 5, we report the mean and standard deviation of per worker trade exposure

[23] Eastern Europe denotes the following countries in our analysis: Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, and the former USSR or its succession states: Russian Federation, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan.

measures (averaged across 92 NACE industries) separately for each of the five panels in our sample. We note several features of the trade data here. First, there has been a dramatic increase in trade exposure of German workers in terms of imports from China and Eastern Europe over time: Imports (in thousands of 2005 Euros per worker) rose from 1.85 in the first panel to 46.46 in the last panel. This increase in imports per worker was accompanied by a corresponding, albeit smaller, increase in exports per worker which, increased from 2.82 to 32.51 thousand Euros per worker during the same period. Overall, while both imports and exports have grown, net imports have risen monotonically over time, with the absolute increase in trade exposure (measured in imports, exports, and net imports) being the largest in the most recent years (especially after the year 2000). Imports (exports) from China rose from 13.56 in 2001-2006 to 28.66 (2.17 to 4.55) in 2007-2012 , and imports per worker from Eastern Europe increased from 13.68 to 17.80 (17.55 to 27.96) in the same period, for a total increase from 27.24 to 46.46 (19.72 to 32.51) thousand Euros per worker. This change corresponds to about doubling of net imports from 7.51 to 13.95 thousand Euros per worker between 2001-06 and 2007-2012 panels. Finally, we note that for both imports and exports per worker, there is substantial cross-sectional variation across industries, as is indicated by the large magnitude of the standard deviation of the trade exposure measures.[24]

Identification

While the documented increase in trade with China and Eastern Europe during this period can to some extent be attributed to factors outside of Germany, such as China's entry to the WTO and to the breakdown of the former Soviet Union ("Fall of the Iron Curtain"), an obvious concern in identifying the causal relationship between exposure to trade and income risk is that domestic demand or productivity shocks, at the industry level, in Germany might be correlated with imports and exports in those industries. To address this concern, we use trade (imports and exports) between China and Eastern Europe, and other high-income countries as instruments for trade exposure of Germany as in Dauth et al. (2014) and Autor et al. (2013). Intuitively, an increase in the competitiveness and external demand from China and Eastern Europe would have resulted in a similar rise in trade volumes between these countries and other high-income countries (as well as vis-a-vis Germany).

The validity of these export flows as instruments for German imports relies on the assumption that exports from China and Eastern Europe to other high-income countries are correlated with their exports to Germany but largely uncorrelated with domestic German eco-

[24]More specifically, knitted and crocheted articles ($Imp = 224.00$), TV, radio, and recording apparatus ($Imp = 153.48$), and games and toys ($Imp = 131.54$) were among the industries with the highest import exposure in 2001-2006, while concrete and cement ($Imp = 0.92$), paints and printing ink ($Imp = 0.95$), tobacco products ($Imp = 1.00$) were the least exposed to imports from China and Eastern Europe. During the same panel, tanning and dressing of leather ($Exp = 89.79$), agro-chemical products ($Exp = 64.50$), electricity distribution and control apparatus ($Exp = 44.93$) experienced high export volume per worker, while industries like cutting and finishing of stone ($Exp = 0.46$), concrete and cement ($Exp = 0.91$) and carpentry ($Exp = 1.46$) had very low export intensity.

nomic factors. Similarly, the imports of China and Eastern Europe from these high-income countries can be used as instruments for exports from Germany, under the assumption that they are correlated with each other and are uncorrelated with domestic factors specific to Germany. To satisfy the exclusion restriction in both cases, in constructing the group of "other" high-income countries, we follow Dauth et al. (2014) to exclude all members of the European Monetary Union as well as Switzerland and the US. The "other" countries included in the instrument group are Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom. The instrument for imports and exports, at the industry level, are then calculated as:

$$IVImp_{jp} = \frac{Imports_{jp}^{\text{Other} \leftarrow \text{East}}}{Emp_{jp-1}} \quad \text{and} \quad IVExp_{jp} = \frac{Exports_{jp}^{\text{Other} \rightarrow \text{East}}}{Emp_{jp-1}},$$

where the numerators are other high-income countries' imports from and exports to China and Eastern Europe and Emp_{jp-1} is the employment count in industry j lagged by one panel. Again, for our baseline instruments, we consider the 6-year annual average during each panel. In various robustness checks, we construct the trade measures as of the first year of each panel and consider alternative specifications in which instruments are constructed by normalizing imports and exports with the 1982 employment count.

Table 6 presents first-stage regression results showing the correlations between the instruments and the endogenous variables, the imports and exports per worker. The first-stage estimates come from specifications including panel and industry fixed effects in Columns (1) for imports per worker and (4) for exports per worker; with further time-varying controls including the share of workers in each main educational category and the share of foreign-born workers in Columns (2) and (5), and, additionally, with industry-specific time trends in Columns (3) and (6). As reported in Table 6, the instruments are strongly and positively correlated with the endogenous variables, and the first stage F-statistics in every specification are quite high and substantially exceed the minimum value for the first stage F-statistics of 10, as suggested by Staiger and Stock (1997).

Estimation Results

Table 7 reports second-stage results obtained from the estimation of (5) for the "pooled sample", using the instrumental variables methodology described above. The first three columns report results with risk estimated by filtering out transitory shocks of duration up to two years ($K = 2$). The next three columns are estimated by filtering out transitory shocks that last at most a year ($K = 1$). In each of the specifications, higher levels of imports per worker result in a higher level of risk, whereas higher exports per worker result in a lower level of risk; the signs and magnitudes of the coefficients are quite robust across specifications. The estimated coefficients imply economically significant effects of trade exposure on risk. Estimates from our preferred specification with the full set of fixed effects are included, under $K = 2$, in Column (3). The coefficient estimates imply that the mean increase in imports (of 20,000 Euros per worker between 2000 and 2007 as reported in Table 5) results in a 9 percent increase in income risk, while the mean increase in exports per worker during the same period (of 13,000 Euros per worker), leads to a decline in income risk of about 7 percent. For $K = 1$, the estimates imply similar and slightly smaller impacts: an increase in risk by 5.4 percent with imports and a reduction in risk by 4.4 percent with exports.

Table 8 reports a variety of robustness checks for the estimates presented in Table 7. All specifications include the full set of panel and industry fixed effects, industry-specific time trends, and additional industry-level controls, as in Columns (3) and (6) of Table 7. Given the similarity of the estimates of the coefficients on trade exposure, under $K = 1$ and $K = 2$, we focus our presentation of results with $K = 2$ for the rest of the paper.[25] Column (1) of Table 8 presents OLS estimates of (5) which are slightly smaller in (absolute) magnitude but qualitatively similar to the benchmark IV estimates reported in Column (3) of Table 7. Columns (2) and (3) of Table 8 explore the sensitivity of our benchmark findings to variations in the methodology used to construct Imp_{jp} and Exp_{jp} and the associated instruments. Column (2) presents estimates with employment levels used in the IV construction fixed at their 1982 level instead, and in Column (3), trade measures and instruments are measured as of the beginning of each panel, rather than as an average over the panel. In Column (4), the standard errors are clustered by industry. Finally, in the last column of Table 8, we omit the last panel corresponding to the years surrounding the global financial crisis (the years 2007-2012). The estimates reported in various columns of Table 8 indicate that our findings on imports are robust across these specifications, with higher levels of imports per worker resulting in higher levels of risk for workers employed in that industry. The negative association between exports and risk is less robust, and depending on the specification, quantitatively weaker and with diminished statistical significance.

To account for any cohort effects we discussed in the earlier section, we allow next for the permanent component of risk to vary by entry cohort as well as by industry and panel. In Table 9, we report estimates from specification (6) which include cohort fixed effects in addition to panel and industry fixed effects, industry-specific time trends, and additional controls. Controlling for cohort effects yields estimates that continue to strongly suggest that imports increase risk and exports decrease risk; indeed, our coefficient estimates in Column (1) are larger in magnitude than those in Tables 7 and 8, where we do not account for heterogeneity in risk across cohorts.

The remaining columns of Table 9 explore the robustness of our benchmark results for the cohort sample to variations in the methodology used for trade exposure measures and associated instruments as well as variations in the main specification. Specifically, in Column (2), we report the OLS estimates of (6). In Columns (3) and (4), we present results using

[25] As discussed earlier, using estimates obtained under $K = 2$ allows us to filter out shocks of longer duration than under $K = 1$, but that are not fully persistent. The corresponding results with $K = 1$ are qualitatively similar and are available on request.

alternative ways of constructing the instrumental variables – by fixing the employment levels at 1982 (Column (3)) and using the beginning-of-panel import and export measures instead of using within-panel averages (Column (4)). In Column (5), standard errors are clustered at the industry level. In Column (6), the last panel is omitted. In Column (7), we use the risk estimates with $K = 1$ as the dependent variable. Again, the estimates remain remarkably robust to the variations introduced to the basic specification, both quantitatively and qualitatively.

In sum, the results presented in this section imply a robust causal connection between trade exposure and income risk. We find strong evidence for a positive causal relationship between income risk and imports and (a slightly less robust) negative association between exports and income risk. In studying this association between trade and income risk, however, we have not taken into account the role of worker human capital, and it is to this issue that we turn next.

5 Human Capital and Income Risk

The well-known "specific factors model" of international trade provides clear predictions regarding the impact of trade policy changes on mean returns to factors of production that are (fully) mobile or (fully) specific to a sector. With a lowering of import tariffs in an industry, owners of factors specific in that sector will experience a reduction in their nominal (and real) returns, while changes in the returns to mobile factors which are able to transition out of the sector are ambiguous. In practical settings, factors of production are neither fully mobile nor fully stuck in a sector, but vary in the extent of their sector specificity. When an industry-level shock such as an increase in imports hits an industry, workers who have acquired high levels of industry-specific human capital will differ in terms of the change in their (mean) wages relative to those with lower levels of human capital, depending on their probability of displacement and on their realized post-displacement outcomes. Importantly, the wage outcomes for workers with similar levels of specific human capital are also likely to be heterogeneous – some workers will keep their current jobs or will transition into jobs in which they are able to transfer some or all of their previous work experience, while others will experience job switches in which this is not the case. We focus next on this dispersion in outcomes for workers with similar levels of specific human capital (*ex ante* risk) and, ask whether the increase in risk following an increase in (net) imports we documented in the earlier section, differs across workers with different levels of specific human capital.

To explore these issues empirically, we allow risk in a given industry and panel to vary across workers with different levels of industry-specific human capital. Specifically, we divide workers in a given industry and panel into quartiles based on the level of their industry tenure and expand specification (5) to allow for the coefficient on net imports ($NetImp_{jp}$) to vary across workers in different quartiles of industry-specific human capital. Our specification is:

$$\log \sigma^2_{\varepsilon jpq} = \gamma_p + \gamma_j + \delta_j p + \beta Z_{jpq} + \sum_{i=2}^{4} \gamma^i S^i_{jpq} + \sum_{i=1}^{4} \gamma^i_N \left(NetImp_{jp} \times S^i_{jpq} \right) + \nu_{jpq}, \qquad (7)$$

where the dependent variable, $\sigma^2_{\varepsilon jpq}$, is income risk estimated over panel p for workers employed in industry j and in quartile q of the industry-tenure distribution as of the beginning of panel p. Industry-tenure quartiles are defined based on the distribution of beginning-of-panel industry tenure levels for the sample of workers pooled across industries within each panel.[26] S^i_{jpq} is a dummy variable for the i-th industry-tenure quartile, which take the value of one for quartile $q = i$ $(i = 1, 2, 3, 4)$. The term $\sum_{i=2}^{4} \gamma^i S^i_{jpq}$ captures the fixed effects for industry-tenure quartiles (with $i = 1$ being the omitted category). The interaction terms allow us to evaluate whether the impact of trade on risk that we have documented in the previous section is heterogeneous across workers with different levels of specific human capital and to explore any potential monotonicity (or lack thereof) in outcomes across these groups.

Column (1) of Table 10 presents regression results based on the sample of risk estimates at the panel-industry-quartile level. A few patterns emerge: First, the estimated coefficients on industry-tenure quartile terms are negative and increase monotonically in absolute terms. This implies that in a hypothetical industry in which the value of imports is equal to that of exports (zero net imports) so that the effect of the interaction terms in the specification is zero, workers with higher levels of industry tenure experience lower level of risk: Workers in the second quartile of industry tenure experience risk that is approximately half ($\approx \exp(-0.865) = 0.42$ times) the risk experienced by workers in the lowest quartile, and workers in the third and fourth quartiles experience risk that is about a third (0.31 times) and a quarter (0.25 times) the risk experienced by workers in the lowest industry tenure quartile, respectively. Second, the estimated coefficients on the interaction terms with net imports are positive, suggesting that higher net imports result in higher risk consistent with our findings in the previous section. Importantly, both the magnitude and the precision of estimates of the interaction terms systematically increase with quartiles of industry-tenure. That is, a given increase in net import exposure increases risk for workers with higher levels of industry tenure in that industry more than it does for workers with lower levels of industry tenure. For example, an increase in net imports by forty thousand Euros per worker (roughly corresponding to the difference between 25th and 75th percentile of net imports in 2007-2012) leads a log increase in risk of 0.28 for workers in the top quartile of industry tenure distribution, relative to 0.16 for the second quartile.

In estimates reported in Column (1), we construct industry tenure quartiles across cohorts for the "pooled" sample, without explicitly taking into account the fact that workers in different entry cohorts will have different levels of labor market experience in a given year.

[26] Alternatively, we can define industry-tenure quartiles based on the *within-industry* industry tenure distribution as of the beginning of each panel; our main findings are robust to this alternative definition.

That is, in any panel, lower tenure quartiles will generally include more workers from later entry cohorts relative to workers in earlier entry cohorts. This implies a possible conflation of the impact of experience with that of industry tenure. To address this issue to some extent, we construct industry-tenure quartiles for each panel separately for workers in each cohort (instead of pooling workers across different cohorts together). With this extra cohort dimension, we then estimate income risk at the industry-panel-cohort-(industry) quartile level and modify Equation (7) as follows:

$$\log \sigma^2_{\varepsilon jpcq} = \gamma_p + \gamma_j + \gamma_c + \delta_j p + \beta Z_{jpcq} + \sum_{i=2}^{4} \gamma^i S^i_{jpcq} + \sum_{i=1}^{4} \gamma^i_N \left(NetImp_{jp} \times S^i_{jpcq} \right) + \nu_{jpcq}, \quad (8)$$

where we include cohort fixed effects, γ_c. The coefficient estimates for the industry-specific human capital and their interactions with net imports, then represent within cohort differences in risk across workers with different levels of industry tenure.

Column (2) of Table 10 presents the corresponding estimation results. Our findings are qualitatively unchanged: Risk increases with net import exposure, with workers with high levels of industry tenure experiencing a greater increase in risk than workers with lower levels of human capital.[27] The coefficient estimates on net import interaction terms are larger in magnitude for the cohort sample as compared to that from pooled sample in Column (1). The quantitative implications of the estimates on the net import and industry-tenure interactions are important. In the 2007-12 panel, the mean value of net imports per worker was 13.95 thousand Euros. Given the coefficient estimates in Column (2) of Table 10, we have that, at the mean level of net imports, risk is 15.23 percent *lower* for workers in the fourth quartile of the industry tenure distribution compared to those in the third quartile.[28] In sharp contrast, when we consider the industry at the 90th percentile of net imports (with net imports of about 92.54 thousand Euros per worker), the difference between the third and fourth quartile workers is 16.21 percent.[29] That is, in this top decile of net-importing industries, risk is about 16 percent *greater* for workers in the highest tenure quartile as compared to the third quartile.[30] This quantitative comparison illustrates an important argument of this paper: High levels of industry-specific human capital can be costly, from a risk perspective, for workers in highly trade-exposed industries.

Columns (3)-(6) of Table 10 report results from a battery of robustness checks. Similar to Tables 8 and 9, Column (3) adopts an alternative IV with employment fixed at the 1982 level. Column (4) uses trade measures and instruments as of the beginning of each panel. Column (5) clusters the standard errors at the industry level. Column (6) omits from the

[27] The difference in point estimates for net imports across different industry-tenure quartiles is statistically significant at 5% level.

[28] $13.95 \times (0.012 - 0.008) + (-1.176 + 0.967) = -0.1523$.

[29] $92.54 \times (0.012 - 0.008) + (-1.176 + 0.967) = 0.1621$.

[30] More broadly, workers in industries with net imports of more than 50 thousand Euros per worker who are in the top quartile of industry tenure distribution will experience higher risk compared to workers in the same industry but with lower levels of industry specific human capital.

regression sample the last panel of 2007-2012. Column (7) of Table 10 includes the BIBB centrality measure. With centrality included, the coefficients on net import interaction terms are mostly unchanged, while centrality itself continues to be negatively related to risk.[31] The main findings remain robust across various specifications: workers with high industry tenure enjoy lower levels of risk, absent any net imports exposure, but they tend to be more affected by exposed to net imports.

We turn next to the role occupation-specific human capital plays in the interaction between trade and risk. This is likely to be different from that of the role of industry specificity since trade shocks, in the first instance, affect industries rather than occupations. Thus, with an adverse trade shock to an industry, it is possible that workers with high levels of occupation-specific human capital may be able to transition to jobs (in the same or other industries) that allow them either to remain in their occupation or to switch to a similar occupation just as easily as workers with low levels of occupational specific human capital. We explore the interactions between trade exposure, income risk and occupational tenure in a manner that is analogous to the preceding analysis concerning industry tenure. The estimates reported in Table 11 are from a specification in which we regress the log of income risk on the dummy variables representing different occupational tenure quartiles and their interactions with net imports. As before, we consider two samples: The "pooled" sample, in which occupational tenure quartiles are determined, within any panel, by pooling workers across cohorts and industries and estimate risk separately for each industry-panel-quartile grouping; and the "cohort" sample, in which occupational tenure quartiles are determined for each cohort within any panel and risk is estimated separately for each industry-panel-cohort-quartile grouping.

Column (1) of Table 11 presents the estimates for the pooled sample. Similar to the analysis with industry tenure, we find that workers with greater occupational tenure experience lower risk in the absence of any exposure to net imports. Specifically, the estimated coefficients imply that in a hypothetical industry with zero net imports, workers in the second occupational tenure category experience risk that is 0.48 that of workers in the lowest occupational tenure quartile and workers in the third and fourth tenure quartiles experience risk that is 0.38 and 0.31 that of the lowest quartile, respectively. The estimated coefficients on the interactions of occupational tenure quartiles with trade exposure, while being statistically significant, do not display clear systematic variation across different occupational tenure quartiles. The estimates reported in Column (2) for the cohort sample are similar: Higher occupational specific human capital is associated with lower risk. The coefficient estimates on the interaction terms are quantitatively similar, suggesting a uniform effect of occupation specific human capital on the link between risk and trade exposure. This finding is in sharp contrast with the monotonically increasing coefficients with rising industry tenure reported in Table 10. The robustness checks in Columns (3)-(6) and the inclusion of centrality mea-

[31] The result is robust to the inclusion of the alternative Berufenet centrality measure.

sure in Column (7) do not alter the coefficients on the occupational tenure or the interaction terms by much. Centrality itself remains strongly negatively related to trade and continues to affirm the relevance of general human capital in mitigating labor income risk.

By constructing industry or occupational tenure quartiles at the cohort level, the estimates in Columns (2)-(7) of Tables 10 and 11 refine the pooled sample estimates. However, they too are subject to the criticism that the industry or occupational tenure quartiles in any panel could reflect rather different levels of tenure across cohorts. That is, in a given panel, the highest tenure quartile for older cohorts will have workers with considerably greater industry or occupational tenure than the highest tenure quartile for younger cohorts.[32] To address this issue, we use the "absolute" number of years of tenure as thresholds to define the tenure quartiles: the lowest quartile contains workers with less than 2 years of industry tenure, the second and third quartile includes workers with industry tenure between 2 and 5 years, and between 5 and 10 years, respectively. The highest quartile includes workers with greater than 10 years of industry tenure.[33] The corresponding estimates are presented in Table 12 - Columns (1)-(3) for industry-tenure and in Columns (4)-(6) for occupation tenure - separately for the pooled and the cohort samples. The use of absolute thresholds to define quartiles, while conceptually meaningful, does not alter the estimates substantially: Absent any exposure to net imports, risk remains lower for workers with higher industry tenure while the coefficients on the net import interaction terms remain higher for higher industry tenure workers. Further, workers with greater occupational tenure also experience lower risk. However, the interaction terms with trade exposure do not differ much across different quartiles, suggesting a relatively uniform effect of occupation specific human capital on the causal links between risk and trade.[34]

For reasons we have discussed earlier, the difference in the findings concerning links between risk, trade exposure and industry-specific human capital rather than occupation-specific human capital should perhaps not be too surprising. Trade directly affects industries rather than occupations. Following an adverse trade shock, workers with high levels of industry tenure are trapped within the industry to a greater extent than workers with low industry tenure, as they are more likely to face a loss of income in the case of displacement that results in an industry switch. This is not necessarily the case for workers with high levels of occupational tenure in the same industry. To the extent that most occupations are demanded in more than one industry, these workers may not face any greater challenges in transition-

[32]For instance, while the 1983-88 panel includes those with at most 6 years of tenure (those who entered the labor market in 1976), the last panel includes workers with up to 30 years of industry tenure. For the cohort sample analysis, both types of workers will be classified in the top quartile of the industry tenure distribution for that panel.

[33]The cutoffs are picked such that the subsample of each quartile consists of approximately the same number of observations. Our results are robust to alternative cutoff values.

[34]We also consider modified specifications in which we replace the net-imports interaction terms in (7) and (8) with interaction terms on imports and exports separately. Our estimates from this modified specification are consistent with our main findings and also suggest that the interaction between human capital and net imports on income risk largely stems from import competition.

ing away from the industry as compared to workers with low levels of occupational specific human capital. Thus, our results suggest that the role played by specific human capital in determining the causal association between trade exposure and income risk crucially depends on the nature of specificity of the human capital of workers.

6 Conclusion

The role of human capital in enabling workers to manage the risk to their income in open economies has been the subject of considerable academic and policy discussion. In this paper, we have empirically assessed the causal link between trade and individual income risk and studied the role that human capital plays in this relationship using an unusually rich worker-level, longitudinal dataset from Germany, spanning the years 1976 to 2012.

We find considerable variation in the magnitude of income risk to which different categories of workers are exposed. Indeed, our estimates suggest substantial heterogeneity in labor income risk across workers in different entry cohorts, over workers' life cycles, and across workers with different levels of industry- and occupation-specific human capital. We find that trade exposure is a causal driver of income risk: Within-industry changes in imports and exports (per worker) are strongly and causally related to income risk, with imports increasing (and exports decreasing) risk. In studying the causal link between trade and income risk, we find an important and complex role for human capital. While, on average, individuals with higher levels of industry- or occupation-specific human capital experience lower income risk, a given increase in net-import exposure in an industry increases risk for workers with higher levels of industry tenure more than it does for workers with lower levels of industry tenure. For workers in highly trade-exposed industries, higher levels of industry-specific human capital can therefore be a liability, from an income-risk perspective.

Our findings suggest that globalization can adversely affect the incentives for human capital accumulation (of industry-specific human capital, in particular) through the income risk channel. This has obvious implications for aggregate, long-term, economic growth whose assessment is an important issue that remains unexplored in this paper but that we leave for future research.

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A Appendix

A.1 The Construction of Occupational Centrality Measures

We construct two centrality measures based on occupation-level task information from two different data sources. The Berufenet dataset is based on expert views. It contains for each occupation a five-dimensional vector corresponding to five categories of tasks: analytical non-routine, interactive non-routine, cognitive routine, manual routine, and manual non-routine tasks. The BIBB dataset is based on worker-level surveys conducted in multiple rounds during our sample period (1986, 1992, 1999, and 2006). Our measure is based on the 1999 survey restricted to the workers in former West German regions.[35] For each occupation, there is a 13-dimensional vector describing the intensity of 13 tasks performed at the workplace:[36] training and teaching, advising, measuring and testing, monitoring, and controlling machines, repairing, buying and selling, organizing and planning, advertising, and marketing, collecting information, negotiating, research and development, manufacturing, and personal care.[37]

Taking the average across workers for each occupation, we obtain the occupation-level task vector. Denote by $\tau_o = (\tau_o^1, \tau_o^2, \cdots, \tau_o^n)$ the task vector for occupation "o" where n stands for the number of tasks ($n = 5$ for the Berufenet dataset and $n = 13$ for the BIBB dataset). For a given worker i, at any given point in time t, we can define the n-dimensional cumulative task profile for this worker as:

$$\rho_{it} = (\rho_{it}^1, \rho_{it}^2, \cdots, \rho_{it}^n) = \left(\sum_{o \in O} (e_{o,it} \times \tau_o^1), \sum_{o \in O} (e_{o,it} \times \tau_o^2), \cdots, \sum_{o \in O} (e_{o,it} \times \tau_o^n) \right),$$

where O is the entire set of occupations in the economy and $e_{o,it}$ is the cumulative number of quarters the worker i has spent in occupation o up to time t. With this cumulative task profile, we can calculate for each worker at any point in time the similarity between his task profile and the task requirement for each occupation. The similarity is defined as the standard

[35] The centrality measures constructed from different survey waves are highly correlated with each other (correlation above 0.6 for most cases). In principle, we can combine multiple waves of the survey to create time-varying task vectors at the occupation level. However, time-varying task vectors can cause discontinuous change in similarity measures over time, and therefore, we stick to the same wave of the survey to ensure consistency.

[36] Alternatively, we can classify the 13 tasks into the five categories as in the Berufenet dataset. It turns out that the resulting centrality measure is highly correlated with our baseline measure (correlation around 0.8). To capture the recursiveness of task-based similarity, we also consider an eigenvector-based centrality measure, which is almost colinear with the baseline measure at the occupation level (correlation above 0.99).

[37] Berufenet- and BIBB-based centrality measures are only modestly correlated with each other (correlation below 0.5), but it is reassuring that both centrality measures yield the same results in our main empirical specification.

angular separation measure:

$$s_{o,it} = \frac{\sum_{j=1}^{n}(\rho_{it}^{j} \times \tau_{o}^{j})}{\sqrt{\sum_{j=1}^{n}(\rho_{it}^{j})^2 \times \sum_{j=1}^{n}(\tau_{o}^{j})^2}}.$$

The occupational centrality measure is then defined as the average similarity between the task profile and all the occupations weighted by the economy-wide employment share:

$$Centr_{it} = \sum_{o \in O}(s_{o,it} \times w_{o,t}),$$

where $w_{o,t}$ is the employment share of occupation o at time t.

Moreover, the task tenure for worker i with occupation o is defined as:

$$Task\_Tenure_{o,it} = \frac{\sum_{j=1}^{n}(\rho_{it}^{j} \times \tau_{o}^{j})}{\sum_{j=1}^{n}(\tau_{o}^{i})^2}.$$

If a worker is in occupation o throughout his career, then the task tenure is the same as total labor market experience. However, if a worker's cumulative task profile is very distant from the task requirement of his current occupation as measured by the angular separation measure, then task tenure can be a lot smaller than the general experience.

Table 1: Summary Statistics of Human Capital Measures (Pooled Sample)

Panel	Number of Cohorts	Total Number of Workers	Experience	Industry Tenure	Occupation Tenure	Centrality (BIBB)
1983-1988	4	485,934	9.73 (8.32)	7.06 (7.59)	7.17 (7.63)	0.77 (0.06)
1989-1994	7	905,511	19.39 (15.06)	13.35 (13.68)	13.44 (13.58)	0.77 (0.06)
1995-2000	10	1,066,378	32.40 (21.43)	22.63 (19.83)	22.45 (19.42)	0.77 (0.07)
2001-2006	13	1,200,697	45.41 (28.04)	30.56 (26.77)	30.87 (26.04)	0.77 (0.08)
2007-2012	16	1,276,876	58.48 (34.81)	39.90 (33.11)	39.68 (32.45)	0.77 (0.08)

Notes: (1) The reported means and standard deviations are based on the human capital measures of all the workers in the pooled sample for each panel. (2) The human capital measures (experience, industry and occupational tenure) are in quarters as of the beginning of each panel. (3) Standard deviations are in parentheses.

Table 2: Risk Estimates (Pooled Sample)

Panel	Risk ($K = 2$ years)	Risk ($K = 1$ year)
1983-1988	0.0033 (0.0017)	0.0035 (0.0016)
1989-1994	0.0027 (0.0019)	0.0029 (0.0014)
1995-2000	0.0021 (0.0010)	0.0022 (0.0008)
2001-2006	0.0022 (0.0011)	0.0022 (0.0009)
2007-2012	0.0014 (0.0010)	0.0016 (0.0008)

Notes: (1) The reported means and standard deviations are based on the (quarterly) estimates of the permanent component of income risk across the 92 manufacturing industries (3-digit NACE Rev. 1.0) of each panel for the pooled sample. (2) We employ the baseline Mincer regressions in risk estimation. (3) Standard deviations are in parentheses.

Table 3: Risk Estimates (Cohort Sample)

Panel	Entry Cohort					
	1976	1982	1988	1994	2000	2006
1983-1988	0.0020	0.0062				
1989-1994	0.0015	0.0026	0.0045			
1995-2000	0.0012	0.0013	0.0025	0.0051		
2001-2006	0.0016	0.0016	0.0018	0.0023	0.0095	
2007-2012	0.0011	0.0008	0.0010	0.0012	0.0022	0.0049

Notes: (1) The reported means are based on the (quarterly) estimates of the permanent component of income risk ($K = 2$ years) across the 92 manufacturing industries (3-digit NACE Rev. 1.0) of each panel-cohort pair for the cohort sample. (2) We employ the baseline Mincer regressions in risk estimation.

Table 4: Risk and Human Capital

	Dependent Variable: log(Income Risk) ($K = 2$ years)					
	(1)	(2)	(3)	(4)	(5)	(6)
Industry Tenure 2nd Quartile	-0.708***	-0.720***	-0.741***			
	(0.029)	(0.029)	(0.030)			
Industry Tenure 3rd Quartile	-0.905***	-1.017***	-1.065***			
	(0.042)	(0.048)	(0.059)			
Industry Tenure 4th Quartile	-1.102***	-1.253***	-1.312***			
	(0.041)	(0.050)	(0.060)			
Occupation Tenure 2nd Quartile				-0.597***	-0.575***	-0.587***
				(0.039)	(0.039)	(0.038)
Occupation Tenure 3rd Quartile				-0.748***	-0.816***	-0.816***
				(0.046)	(0.054)	(0.065)
Occupation Tenure 4th Quartile				-0.993***	-1.108***	-1.105***
				(0.044)	(0.057)	(0.075)
Centrality (Berufenet)		-3.806***			-2.434***	
		(0.598)			(0.600)	
Centrality (BIBB)			-6.134***			-3.159**
			(1.238)			(1.348)
Panel FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
N	7,833	7,833	7,833	7,859	7,859	7,859
R^2	0.326	0.330	0.329	0.299	0.301	0.300

Notes: (1) The reported estimates are from OLS regressions weighted by the employment count of each industry-panel-cohort-quartile cell. (2) The dependent variable is the log of income risk estimate ($K = 2$ years) at the industry-panel-cohort-quartile level, with the baseline Mincer regressions being employed in risk estimation. (3) For each panel-cohort, we sort workers and define quartiles by the beginning-of-panel industry tenure in Columns (1)-(3) and by the beginning-of-panel occupational tenure in Columns (4)-(6). (4) Standard errors clustered at the industry-panel level are in parentheses. *significant at 10%; **significant at 5%; ***significant at 1%.

Table 5: Summary Statistics of Trade Exposure Measures

Panel	Imports	Exports	Net Imports
1983-1988	1.85 (2.69)	2.82 (7.29)	-0.96 (7.57)
1989-1994	6.14 (10.26)	6.07 (17.34)	0.07 (19.84)
1995-2000	14.30 (21.06)	11.02 (14.02)	3.28 (24.57)
2001-2006	27.24 (38.81)	19.72 (18.33)	7.51 (37.97)
2007-2012	46.46 (86.16)	32.51 (30.00)	13.95 (73.89)

Notes: (1) The reported means and standard deviations are based on the 6-year annual average trade measures (German trade with China and Eastern Europe combined) of each panel across the 92 manufacturing industries (3-digit NACE Rev. 1.0). (2) As an outlier, the industry of pesticides and other agro-chemical products (NACE = 242) is excluded in the 1983-88 panel. (3) Standard deviations are in the parenthesis.

Table 6: The First-Stage Regressions (Pooled Sample)

	Imports			Exports		
	(1)	(2)	(3)	(4)	(5)	(6)
IV-Imports	0.386*** (0.035)	0.396*** (0.037)	0.369*** (0.041)	0.035* (0.020)	0.039* (0.021)	0.053** (0.023)
IV-Exports	0.121** (0.056)	0.107* (0.059)	0.105 (0.066)	0.397*** (0.051)	0.388*** (0.050)	0.347*** (0.042)
Panel FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Add Controls	No	Yes	Yes	No	Yes	Yes
Ind-Spec Trend	No	No	Yes	No	No	Yes
(Joint) F-Statistic	34.441	35.157	52.461	34.441	35.157	52.461
N	455	455	455	455	455	455
R^2	0.915	0.921	0.942	0.874	0.877	0.926

Notes: (1) The reported estimates are from the first-stage regression for (5) using the pooled sample ($K = 2$ years), weighted by the employment count of each industry-panel pair. (2) Additional controls ("Add Controls") include the share of workers in each of the six education-training categories and the share of foreign workers. (3) Industry-specific time trend ("Ind-Spec Trend") is constructed at the 2-digit NACE Rev.1 level. (4) Standard errors clustered at the industry-panel level are in parentheses. *significant at 10%; **significant at 5%; ***significant at 1%.

Table 7: International Trade and Income Risk (Pooled Sample)

	Dependent Variable: log(Income Risk)					
	$K = 2$ years			$K = 1$ year		
	(1)	(2)	(3)	(4)	(5)	(6)
Imports	0.004***	0.003***	0.005***	0.003***	0.002***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Exports	-0.009***	-0.008***	-0.005**	-0.006***	-0.005***	-0.004**
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Panel FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Add Controls	No	Yes	Yes	No	Yes	Yes
Ind-Spec Trend	No	No	Yes	No	No	Yes
N	455	455	455	456	456	456
R^2	0.772	0.797	0.824	0.869	0.889	0.909

Notes: (1) The reported estimates are from the 2SLS estimation of (5) using the pooled sample, weighted by the employment count of each industry-panel pair. (2) Additional controls ("Add Controls") include the share of workers in each of the six education-training categories and the share of foreign workers. (3) Industry-specific time trend ("Ind-Spec Trend") is constructed at the 2-digit NACE Rev.1 level. (4) Standard errors clustered at the industry-panel level are in parentheses. *significant at 10%; **significant at 5%; ***significant at 1%.

Table 8: International Trade and Income Risk (Pooled Sample): Robustness

	Dependent Variable: log(Income Risk) ($K = 2$ years)				
	(1)	(2)	(3)	(4)	(5)
	OLS	IV Weights at 1982	Beg-of-Panel Trade	Cluster by Industry	Last Panel Omitted
Imports	0.004***	0.006***	0.005***	0.005***	0.005***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Exports	-0.005***	-0.003	-0.007**	-0.005*	0.004
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
Panel FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Add Controls	Yes	Yes	Yes	Yes	Yes
Ind-Spec Trend	Yes	Yes	Yes	Yes	Yes
N	455	455	455	455	365
R^2	0.824	0.821	0.821	0.824	0.755

Notes: (1) The reported estimates are the robustness checks of (5) using the pooled sample, weighted by the employment count of each industry-panel pair. (2) Additional controls ("Add Controls") include the share of workers in each of the six education-training categories and the share of foreign workers. (3) Industry-specific time trend ("Ind-Spec Trend") is constructed at the 2-digit NACE Rev.1 level. (4) Column (1) reports the OLS estimates; Column (2) reports the 2SLS estimates with the industry-level employment in IV fixed at the 1982 level; Column (3) uses trade exposure measures and the corresponding IVs as of the beginning of the panel; Column (4) has the standard errors clustered at the industry-level; Column (5) omits the last panel. (5) Standard errors clustered at the industry-panel level (except for Column (4)) are in parentheses. *significant at 10%; **significant at 5%; ***significant at 1%.

Table 9: International Trade and Income Risk (Cohort Sample)

	Dependent Variable: log(Income Risk)						
	$K = 2$ years						$K = 1$ year
	(1) Baseline IV	(2) OLS	(3) IV Weights at 1982	(4) Beg-of-Panel Trade	(5) Cluster by Industry	(6) Last Panel Omitted	(7) Baseline IV
Imports	0.007***	0.005***	0.010***	0.007***	0.007***	0.007***	0.005***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Exports	-0.011***	-0.007***	-0.011***	-0.012***	-0.011***	-0.013*	-0.007***
	(0.003)	(0.002)	(0.004)	(0.003)	(0.003)	(0.007)	(0.003)
Panel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind-Spec Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,934	3,934	3,934	3,934	3,934	2,780	4,142
R^2	0.584	0.585	0.583	0.583	0.584	0.576	0.694

Notes: (1) The reported estimates are based on the estimation of (6) using the cohort sample, weighted by the employment count of each industry-panel-cohort cell. (2) Additional controls ("Add Controls") include the share of workers in each of the six education-training categories and the share of foreign workers. (3) Industry-specific time trend ("Ind-Spec Trend") is constructed at the 2-digit NACE Rev.1 level. (4) The dependent variable is income risk with $K = 2$ years for Columns (1)-(6) and that with $K = 1$ year for Column (7). Columns (1) and (7) are baseline 2SLS estimates; Column (2) reports the OLS estimates; Column (3) reports the 2SLS estimates with the industry-level employment in IV fixed at the 1982 level; Column (4) uses the trade exposure measures and the corresponding IVs as of the beginning of each panel; Column (5) has the standard errors clustered at the industry-level; Column (6) omits the last panel. (5) Standard errors clustered at the industry-panel level (except for Column (5)) are in parentheses. *significant at 10%; **significant at 5%; ***significant at 1%.

Table 10: International Trade and Income Risk by Industry-Tenure Quartile

	Dependent Variable: log(Income Risk) ($K = 2$ years)						
	Pooled	Cohort Sample					
	(1) Baseline IV	(2) Baseline IV	(3) IV Weights at 1982	(4) Beg-of-Panel Trade	(5) Cluster by Industry	(6) Last Panel Omitted	(7) BIBB Centrality
Net Imports × Ind-Tenure Q1	0.004	0.005	0.007*	0.007	0.005	0.004*	0.005
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.002)	(0.003)
Net Imports × Ind-Tenure Q2	0.004	0.007**	0.007**	0.009**	0.007**	0.006***	0.007**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)
Net Imports × Ind-Tenure Q3	0.006**	0.008**	0.010**	0.010***	0.008**	0.008***	0.008**
	(0.002)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Net Imports × Ind-Tenure Q4	0.007***	0.012***	0.014***	0.015***	0.012***	0.009*	0.011***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.003)
Ind-Tenure Q2	-0.865***	-0.682***	-0.685***	-0.680***	-0.682***	-0.717***	-0.694***
	(0.048)	(0.031)	(0.032)	(0.032)	(0.030)	(0.035)	(0.033)
Ind-Tenure Q3	-1.161***	-0.967***	-0.965***	-0.968***	-0.967***	-1.056***	-1.022***
	(0.078)	(0.047)	(0.046)	(0.045)	(0.046)	(0.049)	(0.066)
Ind-Tenure Q4	-1.384***	-1.176***	-1.172***	-1.178***	-1.176***	-1.274***	-1.250***
	(0.105)	(0.068)	(0.066)	(0.066)	(0.074)	(0.068)	(0.091)
Centrality (BIBB)							-3.627**
							(1.821)
Panel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Ind-Spec Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,587	7,833	7,833	7,833	7,833	5,365	7,833
R^2	0.676	0.354	0.353	0.353	0.354	0.388	0.355

Notes: (1) The reported estimates are based on the estimation of (7) and (8) using the pooled and cohort sample, weighted by the employment count of each industry-panel(-cohort)-quartile cell. (2) Additional controls ("Add Controls") include the share of workers in each of the six education-training categories and the share of foreign workers. (3) Industry-specific time trend ("Ind-Spec Trend") is constructed at the 2-digit NACE Rev.1 level. (4) The dependent variable is income risk with $K = 2$ years by quartiles of the beginning-of-panel industry tenure at the industry-panel-quartile level for Column (1) and at the industry-panel-cohort-quartile level for Columns (2)-(7). Columns (1) and (2) are baseline 2SLS estimates; Column (3) reports the 2SLS estimates with the industry-level employment in IV fixed at the 1982 level; Column (4) uses the trade exposure measures and the corresponding IVs as of the beginning of each panel; Column (5) has the standard errors clustered at the industry-level; Column (6) omits the last panel; Column (7) includes additionally the BIBB centrality measure in the baseline 2SLS regression. (5) Standard errors clustered at the industry-panel level (except for Column (5)) are in parentheses. *significant at 10%; **significant at 5%; ***significant at 1%.

Table 11: International Trade and Income Risk by Occupation-Tenure Quartile

	Dependent Variable: log(Income Risk) ($K = 2$ years)						
	Pooled	Cohort Sample					
	(1) Baseline IV	(2) Baseline IV	(3) IV Weights at 1982	(4) Beg-of-Panel Trade	(5) Cluster by Industry	(6) Last Panel Omitted	(7) BIBB Centrality
Net Imports × Occ-Tenure Q1	0.009***	0.006*	0.009***	0.008*	0.006*	0.004*	0.006*
	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)	(0.002)	(0.003)
Net Imports × Occ-Tenure Q2	0.006*	0.005*	0.006**	0.008**	0.005	0.007***	0.005*
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Net Imports × Occ-Tenure Q3	0.011***	0.006**	0.009**	0.008**	0.006*	0.004	0.006**
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Net Imports × Occ-Tenure Q4	0.006**	0.006**	0.008**	0.007**	0.006*	0.004	0.007**
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Occ-Tenure Q2	-0.739***	-0.536***	-0.541***	-0.535***	-0.535***	-0.584***	-0.525***
	(0.056)	(0.041)	(0.040)	(0.040)	(0.040)	(0.045)	(0.040)
Occ-Tenure Q3	-0.963***	-0.677***	-0.677***	-0.681***	-0.677***	-0.754***	-0.728***
	(0.090)	(0.057)	(0.055)	(0.055)	(0.068)	(0.066)	(0.067)
Occ-Tenure Q4	-1.164***	-0.889***	-0.895***	-0.897***	-0.889***	-0.984***	-0.986***
	(0.116)	(0.067)	(0.065)	(0.065)	(0.079)	(0.072)	(0.084)
Centrality (BIBB)							-3.552**
							(1.488)
Panel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Ind-Spec Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,617	7,840	7,840	7,840	7,840	5,381	7,840
R^2	0.669	0.318	0.317	0.318	0.318	0.334	0.319

Notes: (1) The reported estimates are based on the estimation of (7) and (8) using the pooled and cohort sample, weighted by the employment count of each industry-panel(-cohort)-quartile cell. (2) Additional controls ("Add Controls") include the share of workers in each of the six education-training categories and the share of foreign workers. (3) Industry-specific time trend ("Ind-Spec Trend") is constructed at the 2-digit NACE Rev.1 level. (4) The dependent variable is income risk with $K = 2$ years by quartiles of the beginning-of-panel occupational tenure at the industry-panel-quartile level for Column (1) and at the industry-panel-cohort-quartile level for Columns (2)-(7). Columns (1) and (2) are baseline 2SLS estimates; Column (3) reports the 2SLS estimates with the industry-level employment in IV fixed at the 1982 level; Column (4) uses the trade exposure measures and the corresponding IVs as of the beginning of each panel; Column (5) has the standard errors clustered at the industry-level; Column (6) omits the last panel; Column (7) includes additionally the BIBB centrality measure in the baseline 2SLS regression. (5) Standard errors clustered at the industry-panel level (except for Column (5)) are in parentheses. *significant at 10%; **significant at 5%; ***significant at 1%.

Table 12: Trade, Risk, and Specific Human Capital with Explicit Cutoffs

	Dependent Variable: log(Income Risk) ($K = 2$ years)					
	Industry Tenure			Occupational Tenure		
	Pooled	Cohort Sample		Pooled	Cohort Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline IV	Baseline IV	BIBB Centrality	Baseline IV	Baseline IV	BIBB Centrality
Net Imports × Tenure < 2yrs	0.001	0.003	0.003	0.007**	0.008**	0.008**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Net Imports × 2yrs ≤ Tenure < 5yrs	0.002	0.003	0.003	0.007***	0.007***	0.007***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Net Imports × 5yrs ≤ Tenure < 10yrs	0.004	0.008***	0.008***	0.004	0.004	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Net Imports × Tenure ≥ 10yrs	0.007***	0.008***	0.008***	0.006**	0.009***	0.009***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
2yrs ≤ Tenure < 5yrs	-0.809***	-0.758***	-0.758***	-0.612***	-0.592***	-0.599***
	(0.047)	(0.033)	(0.034)	(0.066)	(0.043)	(0.042)
5yrs ≤ Tenure < 10yrs	-1.124***	-1.089***	-1.092***	-0.930***	-0.923***	-0.917***
	(0.065)	(0.035)	(0.039)	(0.091)	(0.048)	(0.049)
Tenure ≥ 10yrs	-1.345***	-1.348***	-1.352***	-1.084***	-1.114***	-1.086***
	(0.097)	(0.057)	(0.062)	(0.152)	(0.081)	(0.092)
Centrality (BIBB)			-0.304			1.425
			(1.467)			(1.579)
Panel FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Add Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	Yes	Yes	No	Yes	Yes
Ind-Spec Trend	Yes	Yes	Yes	Yes	Yes	Yes
N	1,548	7,117	7,117	1,567	7,010	7,010
R^2	0.692	0.416	0.416	0.698	0.383	0.383

Notes: (1) The reported estimates are based on the estimation of (7) and (8) using the pooled and cohort sample, weighted by the employment count of each industry-panel(-cohort)-quartile cell. (2) Additional controls ("Add Controls") include the share of workers in each of the six education-training categories and the share of foreign workers. (3) Industry-specific time trend ("Ind-Spec Trend") is constructed at the 2-digit NACE Rev.1 level. (4) The dependent variable is income risk with $K = 2$ years by quartiles of the beginning-of-panel industry tenure at the industry-panel-quartile level for Column (1) and at the industry-panel-cohort-quartile level for Columns (2)-(3), and by quartiles of the beginning-of-panel occupational tenure at the industry-panel-quartile level for Column (4) and at the industry-panel-cohort-quartile level for Columns (5)-(6). Columns (1)-(2) and (4)-(5) are baseline 2SLS estimates; Columns (3) and (6) includes additionally the BIBB centrality measure in the baseline 2SLS regression. (5) Standard errors clustered at the industry-panel level (except for Column (5)) are in parentheses. *significant at 10%; **significant at 5%; ***significant at 1%.

Table A1: The Mincer Regressions (Pooled Sample)

	Dependent Variable: $100 \times \log(\text{Earnings})$	
Panel	(1)	(2)
Age	5.101***	
	(0.004)	
Age^2	-0.054***	
	(0.000)	
Experience		2.129***
		(0.047)
Experience^2		-0.059***
		(0.000)
Firm Tenure		0.192***
		(0.001)
Ind Tenure		0.382***
		(0.001)
Occ Tenure		0.353***
		(0.001)
Task Tenure		0.489***
		(0.005)
Centrality (BIBB)		-3.454***
		(0.077)
Year-Quarter FE	Yes	Yes
Regional FE	Yes	Yes
Industry FE	Yes	Yes
Occupation FE	Yes	Yes
Education FE	Yes	Yes
N	103,557,457	103,557,457
R^2	0.408	0.422

Notes: (1) The reported estimates are from the OLS estimation of (1) using the pooled sample by pooling all the six-year panels together. (2) All the tenure measures are measured as the beginning of each panel in years. (3) Education fixed effects include the six education-training categories. (3) Standard errors are in parentheses. *significant at 10%; **significant at 5%; ***significant at 1%.