Do Firms Hedge Human Capital?*

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Abstract

When firms choose staffing levels under demand uncertainty, any staffing level implies a level of expected temporarily idle labor (*hoarded labor*). However, hoarded labor has been difficult to measure, and we know little about its implications for corporate financial policies. This paper addresses these gaps by (i) constructing a novel firm-level measure of hoarded labor from German administrative employment data and firms' use of short-time work, and (ii) formalizing and testing a *labor-hoarding channel of risk management.* The idea is that while hoarding labor may be highly profitable during periods of high demand, it also raises the wage bill during periods of low demand and, taken together, thus amplifies cash flow volatility. Risk-averse firms may respond by cutting back risk exposure along other dimensions. We focus on one risk-reduction margin—unhedged foreign exchange (FX) risk—which is a major business risk for the small to medium-sized export-oriented German firms in our sample and must be disclosed in their annual reports. In line with the model, we show that firms that hoard more labor bear less unhedged FX risk. Using instruments based on occupation-specific hiring and training frictions, we provide causal evidence that labor hoarding influences FX hedging decisions.

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1 Introduction

It has long been hypothesized that firms hoard labor (see, e.g., Okun (1963); Biddle (2014)): under demand uncertainty and in the presence of hiring frictions, they choose staffing levels that imply an amount of expected temporarily idle labor (*hoarded labor*). Such labor-hoarding behavior has important macroeconomic implications for unemployment (Giroud and Mueller, 2017) and labor productivity (Oi (1962); Clark (1973); Rotemberg and Summers (1990); Burnside, Eichenbaum, and Rebelo (1993). Yet, unlike more conventional buffers such as cash holdings or unused debt capacity, excess labor held idle is very difficult to measure (see, e.g., Fay and Medoff (1985)). Moreover, very little is known about its implications for corporate finance.

In this paper, we use rich administrative data to document firms' labor hoarding and study the implications of hoarded labor for corporate financial policies. First, we construct a novel firm-level measure of hoarded labor based on German matched employer-employee data, inferring firms' typical idle labor from their use of short-time work in periods when a broad set of firms—including firms with normal operations—were eligible for the program. Second, we study the causal effect of labor hoarding on firms' financial behavior using instruments that exploit occupation-specific drivers of hoarding (labor-market shortages and firm-specific training). We find causal evidence that firms' labor hoarding affects their financial hedging choices—what we refer to as a *labor-hoarding channel of risk management*.

The mechanism underlying this channel is that labor hoarding creates an option-like payoff for the firm: holding additional workers can be very valuable at times of high demand but raises risk overall (similar to Hackbarth and Johnson (2015) for capital). If firms could hire workers with the required skills and firm-specific knowledge exactly when demand picks up, there would be no incentive to hoard. However, in the presence of hiring frictions, this may not be feasible. Instead, hoarded labor gives firms the option to respond quickly in periods when demand is high—precisely when there may be scope for price increases (Boehm and Pandalai-Nayar, 2022), rendering these times particularly profitable. The flip side is that maintaining a larger workforce raises the wage bill even at times of low demand, amplifying operating leverage and cash flow volatility (Simintzi, Vig, and Volpin, 2015; Donangelo, Gourio, Kehrig, and Palacios, 2019). Understanding whether firms respond to this heightened cash flow volatility due to hoarded labor by taking less risk in other parts of their business matters because the margins on which they may scale back risk-taking are wide-ranging and include activities such as risky R&D that are central to innovation and firm dynamism.

Firms' risk management polices are hard to measure, however, and focusing on small- to medium-sized firms (SMEs) in Germany allows us to overcome this second measurement challenge. We focus on foreign exchange (FX) risk, which is a major business risk for the export-oriented high-tech manufacturing sector in Germany,[1] while firms are required to report on the unhedged portion as well as hedging strategies in their annual reports. In the baseline specification, we then find that a one-standard-deviation increase in hoarded labor (corresponding to 5 percent of the workforce being idle on average) leads to a reduction in unhedged FX risk by 0.6 standard deviations.

We start with a stylized model we develop to formalize the mechanism and to conceptually guide the empirical analysis later. The two-period model features two distinct risks: uncertainty about product demand and an unrelated price risk, e.g., arising from the exchange rate for an exporting firm, which can be hedged ex ante at a cost. As in Arellano, Bai, and Kehoe (2019), the key friction is that firms—to varying degrees—rely on workers who must be hired before demand is known (*fixed labor*). The amount of fixed labor determines the firm's production capacity in period two, and, crucially, we can explicitly define *hoarded labor* as the implied level of expected unused fixed labor. Up to the optimal level, higher capacity increases expected cash flows but also raises the default probability. We show that for a risk-averse firm—as a private SME facing financing frictions likely is, (Froot, Scharfstein, and Stein, 1993)—this generates a trade-off that induces the firm to hedge the price risk, thereby reducing its unhedged exposure. In the model, firms' reliance on fixed labor (their degree of *firm-specific human capital*) is exogenous, and heterogeneity in this dimension drives different capacity and subsequently labor-hoarding choices.

We bring the model to the data by assembling an extensive dataset that combines information on FX hedging with granular information on monthly unused hours for the universe of establishments in Germany that can be linked to firm-level financial information. On the financial side, for these overwhelmingly private companies, we enrich information on balance sheets, income statements, and

1 For example, *FLEXIM Flexible Industriemesstechnik GmbH* states in its 2012 annual report that "EUR/USD exchange rate fluctuations are a major risk, as price adjustments are not feasible. 42% (37% in the previous year) of our revenues are USD-denominated" (authors' translation).

bank relationships with information on their FX hedging strategies as extracted via text analysis of annual reports. On the labor side, we have matched employer-employee data from social security records, as well as granular information on unused employee hours at a monthly frequency whenever firms utilize short-time work.

To measure hoarded labor, we exploit two episodes when the government dramatically relaxed access restrictions to the short-time work (STW) scheme, allowing a broad set of firms to enter the scheme and thereby providing incentives for them to document in detail monthly unused hours per employee. STW is a job retention scheme aimed at overall healthy firms with temporary economic difficulties (Giupponi and Landais, 2023; Cahuc, 2024). It enables firms admitted to the scheme to flexibly reduce hours, which must be documented in detail, while employees are compensated for most of the resulting wage loss. Access is typically very restricted, but in 2009 and again in March 2020, the government suddenly eased the rules by decree, suspending the requirement that at least one third of employees be affected and that alternative measures, such as working-time accounts, be exhausted first. We conduct a survey at eight local branches of the employment agency to confirm that access restrictions were minimal in 2020.

From the raw data, we see that firms use STW in 2020 to receive wage subsidies also for unused labor they would have temporarily had anyway, which is the basis of the measure. In the raw data, for firms with a year-on-year revenue drop, the size of the drop aligns well with the increase in average STW utilization; yet firms with a revenue increase also show substantial STW utilization unrelated to the revenue change—revealing temporarily idle labor during normal operations. We control for year-on-year revenue change as a proxy for COVID-related capacity underutilization, and define a firm's level of hoarded labor as the residual average STW intensity in the second half of 2020. To further reduce COVID-related capacity underutilization embedded in the measure, we focus on a segment of the economy that was arguably less affected by the COVIV-19 shock; by excluding data from the lockdown months up to May 2020 and from January 2021 onwards; by excluding firms with a revenue change below –20% or above 20%; and by focusing (due to FX data availability) on the tradable-goods sector which is less reliant on personal interactions.

In a first step, we examine firm characteristics correlated with higher levels of hoarded labor and, focusing on the role of demand uncertainty for hoarded labor, demonstrate that labor hoarding strengthens the comovement of profitability with demand. Firms that hoard more labor are somewhat smaller, which is consistent with limited access to internal labor markets that larger firms have access to (Cestone, Fumagalli, Kramarz, and Pica, 2024). They do not statistically significantly differ in terms of cash holdings and leverage but have a lower return on assets. This likely reflects residual negative selection into STW (Giupponi and Landais, 2023) even under relaxed access; we therefore control for ROA and value added in robustness checks. Second, in a firm-year panel between 2010 and 2020, we document that changes in profitability co-move more strongly with industry-wide upturns and downturns for labor-hoarding firms compared to their non-labor-hoarding counterparts, consistent with hoarded labor increasing volatility.

To explore the link between hoarded labor and risk management, in the main analysis, we examine whether higher levels of hoarded labor are associated with higher firm-level CF volatility, measured as the standard deviation of cash flows scaled by revenue over the period 2010-2019. We find that total CF volatility for labor-hoarding firms is similar to that of other firms—the empirical analog of a binding risk-capacity constraint. However, when we narrow the focus to one particular margin of risk adjustment (CF volatility arising from unhedged FX movements), we instead observe a negative correlation. To that end, we construct two measures of FX-induced CF volatility from accounting data on FX transaction income, thereby extending the approach taken in Adams and Verdelhan (2022) to private firms. These measures are net of hedging by construction, and the way the correlation varies across firm characteristics mirrors comparative statics implied by the model.

Although FX hedging may not universally be a primary risk-management tool, it is a particularly natural margin of adjustment for German SMEs engaged in global exports. FX risk arising from foreign-currency-denominated sales can be managed with few operational changes inside the firm, and FX hedging products are widely available through banks. In the predominantly bank-based financing environment of European SMEs, firms in our sample—on average linked to 2.6 banks—have ready access to such instruments. Both for large German banks (Deutsche Bank, Commerzbank, UniCredit) and for regional commercial and savings banks, provision of FX and interest-rate derivatives to clients is a core business activity.[2]

To identify a causal effect of labor hoarding on firms' willingness to bear other risks, we use an

2 We further use text analysis of annual reports from banks that have banking relationships with firms in the sample to extract their year-end amounts of derivatives outstanding with commercial clients. Even for regional and commercial banks, these exceed 15 billion EUR every year.

instrumental-variable strategy that relies on firm-specific human capital as the underlying driver of hoarding. The design follows a shift-share logic with firms' occupational composition as fixed shares and occupation-level onboarding frictions as shocks. We construct instruments that capture different sources of onboarding frictions: one based on so-called shortage occupations, which proxies for long hiring times, and another based on the importance of vocational training in each occupation, which proxies for long training times. Connecting thin labor markets to occupations that require long hiring times is in line with Jäger, Heining, and Lazarus (2024), who find higher replacement costs of firm-specific human capital in thin labor markets.

Using the instrumental-variables approach, we find empirical support for the existence of a labor-hoarding channel of risk management. As hypothesized, the first-stage coefficients for both instruments are positive. The two-stage least squares (2SLS) estimates indicate that a one-standard-deviation increase in hoarded labor lowers FX-induced CF volatility by roughly 0.6 standard deviations when using the shortage occupation-based instrument, and by about 1.5 standard deviations with the vocational training-based instrument. The fact that 2SLS estimates are larger in magnitude than the corresponding OLS estimates is consistent with OLS being biased toward zero, due to omitted variables such as firms' underlying risk-management sophistication.

To strengthen the evidence on firms' hedging behavior, we further construct two hedging measures based on text analysis of hand-collected firms' annual reports. The first is a keyword-based measure of FX-derivatives usage; the second is an AI-based measure of active FX risk management that also captures broader operational hedging strategies.[3] Given the scarcity of data on FX-derivatives usage by non-financial firms, we first present some stylized facts on the difference between derivatives-users vs. non-users: Non-users are smaller and hold more liquidity (as in Lyonnet, Martin, and Mejean (2022)), while FX-derivatives usage appears to be more targeted towards exports than imports. We then examine heterogeneity across firms using both the measures and find that firms reporting active management of their FX exposure indeed drive the effect.

The phenomenon that labor hoarding affects firms' risk tolerance in other areas is likely not unique to Germany. The trade-off around staffing levels also appears in the U.S. Quarterly Survey of Plant Capacity Utilization, where the leading reasons for operating below full production capability

3 To shed light on the types of operational hedging strategies employed, we manually classify strategies for a subset of firms based on the five most relevant sentences from the annual reports on which the AI-based indicator is built.

are insufficient orders (low demand and idle labor) and insufficient labor supply (high demand and onboarding frictions) (Appendix Figure C.1). In Europe, stronger employment protection legislation limits firms' ability to adjust by laying off workers after adverse demand realizations (as in Bentolila and Bertola (1990)), making ex-post hoarded labor more difficult to shed than in the U.S. This rigidity should, if anything, increase the importance of carefully choosing ex-ante staffing levels for European firms. Understanding to what extent the mere presence of an insurance scheme such as STW, even in its strict-access form, encourages (ex-ante) labor hoarding at the aggregate level and the implications thereof, is a relevant question but beyond the scope of this paper.

Our paper contributes to several strands of literature. By introducing a new firm-level measure of hoarded labor, it connects to the literature on measuring labor hoarding dating back to the 1960s (see Biddle (2014) for an overview). Our measure builds on short-time work policies, which have been studied in various contexts (see, e.g., (Giupponi and Landais, 2023; Cahuc, 2024; Brinkmann, Jäger, Kuhn, Saidi, and Wolter, 2024; Kagerl, 2024; Kuo, 2024)). Survey evidence on firms' use of STW during COVID-19, as in Kuhn, Luo, Manovskii, and Qiu (2023), highlights the potential to learn about labor hoarding at the firm level during this episode—the approach taken in this paper.

Second, it adds to the literature studying the implications of fixed labor expenses (Donangelo, Gourio, Kehrig, and Palacios, 2019; Dhyne, Kikkawa, Komatsu, Mogstad, and Tintelnot, 2025; Acabbi and Alati, 2021) and the role of labor for corporate financial policies in particular (see, e.g., Agrawal and Matsa (2013); Campello, Gao, Qiu, and Zhang (2018); Schmalz (2018); Caggese, Cuñat, and Metzger (2019); Baghai, Silva, Thell, and Vig (2021); Kim (2020)). Prior research has documented that labor-induced operating leverage tends to crowd out financial leverage (Simintzi, Vig, and Volpin, 2015; Serfling, 2016; Kuzmina, 2023; Favilukis, Lin, and Zhao, 2020), but comparatively little attention has been paid to adjustments on the asset side, which is the focus here. An exception is Ghaly, Anh Dang, and Stathopoulos (2017), who show that firms relying more on skilled labor hold higher cash balances. This paper extends the analysis of asset-side adjustments, focusing on the role of hoarded labor, which acts like a costly real option not just as downside risk.

Third, this paper contributes to the large literature on firms' hedging (see, e.g., Stulz (2024) for a recent overview) where the determinants of FX hedging by non-financial firms are still not fully understood (Alfaro, Calani, and Varela, 2024, 2021; Levin-Konigsberg, Stein, Averell, and Castañon, 2023; Adams and Verdelhan, 2022). Huang, Huang, and Zhang (2019) provide a first link to labor decisions by examining how public firms' commitment to employee benefits, as captured by an employee-treatment score, affects the fraction of foreign sales hedged with derivatives. In this paper, we show that labor hoarding is a contributor to firms' FX hedging motives and, by assembling a new dataset on FX-derivatives usage, shed light on the prevalence of financial and operational hedging strategies among German SMEs.

The remainder of the paper is organized as follows. Section 2 presents the model. Section 3 describes the construction of the measure for hoarded labor and provides institutional context of STW in Germany. Section 4 introduces the datasets we use for our empirical analysis. Section 5 tests the measure against intuition along different dimensions. Section 6 provides a link to unhedged FX risk using correlations, while Section 7 contains the results drawing on an instrumental-variables approach. Section 8 presents evidence on FX hedging strategies. The last section concludes.

2 Mechanism in a Stylized Model

We formalize a labor-hoarding channel of risk management in a stylized model that is similar to the example in Arellano, Bai, and Kehoe (2019) but innovates along three dimensions. First, it introduces an additional price risk. Second, it explicitly models hoarded labor, allowing a close mapping to the data and subsequent empirical analysis. Third, it incorporates firm-specific human capital as a source of firm heterogeneity underlying different levels of hoarded labor.

The key risk trade-off in the model is illustrated in Panel (a) of Figure 1. A firm faces demand uncertainty and uncertainty around an unrelated price risk, which can be hedged at a cost. Ex ante, the firm needs to choose a level of fixed labor that sets its production capacity. More fixed labor raises expected CF but also increases the default probability. If the firm is risk-averse (Froot, Scharfstein, and Stein, 1993) and needs to maintain a default probability below some threshold, it offsets the increase in default probability from more fixed labor by hedging the price risk more extensively.

2.1 Setup and Definition of Hoarded Labor

Consider a firm that produces a good or service sold at a price normalized to 1. It operates in the following two-period environment.

Demand uncertainty. The firm employs two types of workers: workers with specialized knowledge or training who need to be hired in advance (*fixed labor*) and workers who can be employed flexibly depending on demand (*variable labor*). A firm is characterized by a level of *firm-specific human capital* $\gamma \in [\gamma_{min}, \gamma_{max}]$, fixed by their technology, which determines the relative importance of fixed labor in the production process. Specifically, a firm with γ requires γc fixed labor and $(1-\gamma)c$ variable labor to produce output c.

In $t = 0$, firm γ chooses its fixed labor γc and consequently *capacity* c under demand uncertainty. In $t = 1$, the firm receives *orders* $X \sim \mathcal{N}(\mu, \sigma^2)$.[4] The firm serves orders up to its chosen capacity c, producing $\min(X, c)$. The firm knows the expectation μ and variance σ^2 of the normally distributed random variable X with cdf F. No capital exists, and the wage per unit of labor is $w \in [0, 1]$.

Price uncertainty. The firm faces a second type of uncertainty: unrelated price risk, which is realized in $t = 1$. To fix ideas, suppose the firm exports at a price denominated in foreign currency. Let Y be the value in the firm's home currency, a discrete random variable equal to 1 in expectation that takes three values: for some fixed $a \in (0, 1)$, $P[Y = (1-a)] = P[Y = (1+a)] = p$ and $P[Y = 1] = 1 - 2p$, for $p \in [0, 1/2]$. Thus, $Var[Y] = 2pa^2$. X and Y are independent.[5]

The firm has access to a hedging tool against exchange-rate fluctuations. In $t = 0$, the firm chooses a *hedge level* $h \in [0, h_{max}]$, $h_{max} \leq a$, and is subsequently not exposed to Y, but to a *hedged exchange rate* $\tilde{Y}$ with $P[\tilde{Y} = 1 - (a-h)] = P[\tilde{Y} = 1 + (a-h)] = p$ and $P[\tilde{Y} = 1] = 1 - 2p$. Let $K(h)$ be the per-unit costs associated with hedge level h such that no hedging is costless, $K(0) = 0$, and higher levels of hedging are associated with higher costs, $K' > 0$. Specifically, let $K(h) = kh$ with $k \in (0, 1)$.

Optimization problem. Cash flow $CF_\gamma(c, h)$ in $t = 1$ for a firm γ is

$$CF_\gamma(c, h) := \min(X, c)\left[\tilde{Y} - kh - (1-\gamma)w\right] - \gamma wc - b, \tag{1}$$

4 We assume X has little mass below zero; that is $\mu >> \sigma$ (see Assumption A1). Formally, one can consider a normal distribution truncated at zero. The core solution technique also holds for a truncated normal distribution but adds technical details without further economic insights.

5 The assumption that demand X and the exchange rate Y are independent reflects a short-run perspective. In practice, over the medium to long term, an appreciation of the home currency (a lower Y) is likely associated with reduced foreign demand (a lower X). A positive comovement between X and Y is expected to intensify the model mechanism.

with $b \geq 0$ some fixed obligations, for example, debt payments due in $t = 1$. In particular, CF is quantity produced, $\min(X, c)$, multiplied by the per-unit price net of costs (expression in brackets), minus the wage bill for fixed labor, γwc, and some other fixed costs b. Importantly, whereas variable labor costs scale with output, fixed labor costs scale with the capacity level set at $t = 0$.

The per-unit hedge costs associated with some hedge level, kh, are assumed to scale with output, not capacity. Therefore, although the firm sets the hedge level h in $t = 0$, it can adjust the hedged volume depending on actual demand. In the case of a financial hedge using FX derivatives, an example of such an arrangement is a baseline agreement with the firm's relationship bank to hedge a specific fraction of revenue (hedge level), with the notional amount adjustable once demand is known (costs scale with output). For an operational hedging strategy, it may correspond to a situation in which the firm ex-ante requires a certain fraction of output to be invoiced in its home currency (hedge level), weakening its bargaining position with customers and resulting in a reduced margin (costs scale with output).

The firm has limited risk-bearing capability and needs to maintain a default probability in the bad realization of the exchange rate below some threshold α.[6] Hence, a firm γ solves the following optimization problem:

$$\max_{c,h} E[CF_\gamma] \quad \text{s.t.} \quad P[CF_\gamma < 0 | Y = (1-a)] \leq \alpha. \tag{2}$$

Hoarded labor. *Hoarded labor (hl)* is defined as expected unused fixed labor. That is, for a firm with firm-specific human capital γ that chooses capacity c,

$$hl_\gamma(c) := \gamma \left(c - E[\min(X, c)] \right). \tag{3}$$

A firm that hired γc fixed labor expects to need $\gamma E[\min(X, c)]$ fixed labor for production. The difference, as in (3), represents expected unused fixed labor. Therefore, the sum of labor used in

6 We derive the model solution analytically for the constraint in (2). In the numerical simulation, we also consider the (more intuitive) constraint $P[CF_\gamma < 0] \leq \alpha$ (see Appendix Figure C.2) with little change in the result. This constraint is stricter because it demands that the overall probability of default not exceed α. It makes the analytical solution more cumbersome without adding additional insights.

production and hoarded labor equals the size of the workforce; that is,

$$\underbrace{E[\min(X,c)]}_{\text{labor used in production}} + \underbrace{\gamma\,(c - E[\min(X,c)])}_{\text{hoarded labor}} = \underbrace{E[\min(X,c)](1-\gamma)}_{\text{variable labor}} + \underbrace{c\gamma}_{\text{fixed labor}}.$$

This definition aligns with two intuitive features of hoarded labor. First, a firm with no firm-specific human capital ($\gamma = 0$) can flexibly choose employment depending on demand and thus has no hoarded labor. Second, a firm entirely dependent on firm-specific human capital ($\gamma = 1$) cannot hire employees based on demand, so hoarded labor corresponds to unused capacity.

2.2 Analytical Model Solution

We solve the model analytically for a fixed level of firm-specific human capital γ and, as a second step, as a function of γ. As a starting point, consider the firm's unconstrained problem:

$$\max_{c,h} E[CF]. \tag{4}$$

Lemma 1 (**Trade-off behind capacity choice**). *Consider a firm with firm-specific human capital γ. Then, the firm's unconstrained problem* (4) *has a unique solution* $(c^*(\gamma), h^*(\gamma))$ *with*

$$h^*(\gamma) = 0 \tag{5}$$

$$c^*(\gamma) \;\; s.t. \;\; \Big[1-(1-\gamma)w\Big]\Big[1-F\left(c^*(\gamma)\right)\Big] = \gamma w. \tag{6}$$

Proof. See Appendix A1. □

In the absence of the constraint, the firm does not hedge, and the trade-off around capacity choice is intuitive. Hedging has no benefit in expectation, because it does not change the expected exchange rate but is costly. Hence, the firm chooses not to hedge when solely maximizing expected CF. Regarding capacity choice, (6) states that, at the optimum, the expected marginal cost of increasing capacity equals the expected marginal benefit. The marginal cost of increasing capacity is the wage for fixed labor (RHS). The marginal expected benefit (LHS) is the expected price net of variable costs, $(1-(1-\gamma)w)$, times the probability that the firm benefits from the increased capacity, i.e., that orders exceed the current capacity, $(1-F(c^*(\gamma)))$.

Now, we turn to the constrained problem (2), which requires the following set of parameter assumptions:

$$\mu \geq 5\sigma \tag{A1}$$

$$\gamma_{max} < \bar{\gamma}_{max} = (1 - w - kh_{max})/w, \gamma_{max} \leq 1 \tag{A2}$$

$$\gamma_{min} > \bar{\gamma}_{min} = (1 - w)/(9w) \tag{A3}$$

$$a \leq (4/9)(1 - w) - (1/3)kh_{max} \tag{A4}$$

$$k \leq F^{-1}(\alpha)/\sigma(\sqrt{2/\pi} - 3/4)/(3 + F^{-1}(\alpha)/\sigma(\sqrt{2/\pi} - 3/4)) \tag{A5}$$

$$(c - \mu/\mu)\gamma_{max} w < (1 - a - w - b/\mu) - (2/5)(1 - a - w). \tag{A6}$$

Discussion of parameter assumptions. Assumption A1 limits demand volatility by requiring that the standard deviation of the demand distribution does not exceed one-fifth of its expectation. For a normal distribution, this implies a drop in demand by 20% relative to the expected level has a likelihood of less than 16% – still a lot by industry standards. Assumptions A2 and A3 restrict attention to optimal capacity choices above the expected level but below such a high level that demand exceeds capacity in less than 10% of the cases. More formally, they restrict capacity choices to the range $[\mu, \mu + (5/4)\sigma]$. Assumptions A4 and A5 restrict the amplitude of exchange-rate fluctuations and the per-unit costs for hedging. Assumption A6 demands that the fixed costs relative to the profit margin are bounded from above. Specifically, the first term on the RHS of (A6) represents the profit margin when capacity and demand match expectations. The assumption then ensures the profit margin can accommodate some additional costs per unit of production resulting from fixed labor choices that differ from expected demand.

Proposition 1 (**Solution for fixed** γ)**.** *Suppose assumptions A1 - A6. Consider a firm with firm-specific human capital* γ*. Then, a unique solution* $(c^{opt}(\gamma), h^{opt}(\gamma))$ *to* (2) *exists. There are four possible cases:*

a) Either the constraint does not bind, and we get the unconstrained solution from Lemma 1,

b) Or the constraint binds with no hedging, $h^{opt}(\gamma) = 0$*,* *c) Or the constraint binds in an interior solution with*

$$\frac{\partial_c E[CF]}{\partial_c P[CF < 0|Y = (1-a)]} = \frac{\partial_h E[CF]}{\partial_h P[CF < 0|Y = (1-a)]},$$

d) Or the constraint binds with full hedging, $h^{opt}(\gamma) = h_{max}$.

Proof. See Appendix A2. □

The interior solution in Proposition 1 states that capacity and hedging are complements. Increasing capacity and decreasing hedging are both profitable in expectation, but they come with a cost as they raise the default probability. Hence, at the optimum, the shadow costs of increasing capacity equal the shadow costs of decreasing hedging. In other words, more capacity and *less* hedging (both profitable in expectation) compete for scarce risk-bearing capability.

Which case occurs depends on the level of γ. Panels (c)–(e) of Appendix Figure C.3 illustrate the model solution for three increasing levels of γ. In each panel, points that satisfy the relevant conditions (constraint, unconstrained optimality, Lagrange optimality) are depicted in red, yellow, and blue, respectively. As γ increases, the constraint becomes stricter, foreshadowing the next proposition, which characterizes the model solution as a function of γ.

Proposition 2 (**Full model solution**). *Suppose assumptions A1 - A6. Consider a continuum of firms $\gamma \in [\gamma_{min}, \gamma_{max}]$. Then there exist thresholds $\gamma_1 < \gamma_2 < \gamma_3$ such that firms' optimal capacity and hedging choices $(c^{opt}(\gamma), q^{opt}(\gamma))$ are*

$$\begin{cases} \textit{the unconstrained optimum a) in Proposition 1} & \textit{if } \gamma \leq \gamma_1 \\ \textit{the corner solution with no hedging b) in Proposition 1} & \textit{if } \gamma_1 < \gamma \leq \gamma_2 \\ \textit{the interior optimum c) in Proposition 1} & \textit{if } \gamma_2 < \gamma \leq \gamma_3 \\ \textit{the corner solution with full hedging d) in Proposition 1} & \textit{if } \gamma_3 < \gamma. \end{cases} \tag{7}$$

Not all four cases need to occur, for example, if $\gamma_{max} < \gamma_3$.

Proof. See Appendix A3. □

The intuition behind the effect of an increase in γ is as follows. An increase in γ means that, all else equal, a larger fraction of the wage bill is borne as fixed rather than variable costs. Higher fixed costs increase the default probability, making the constraint stricter. Therefore, as γ increases, the solution transitions from unconstrained to constrained.

2.3 Empirical Predictions

Equipped with a characterization of the model solution as a function of γ, we numerically solve the model for a fixed set of parameters and derive testable predictions.

Varying γ. Panels (a) and (b) of Appendix Figure C.3 show that as γ increases, optimal capacity decreases while the optimal choice of fixed labor increases. The intuition behind the decrease in optimal capacity is similar to the key mechanism in Arellano, Bai, and Kehoe (2019). In their model, firms reduce their labor input as demand volatility rises to counteract the increase in default probability associated with the increase in demand volatility. Here, an increase in γ is associated with a higher default probability. Consequently, under a binding constraint, the firm chooses lower capacity. However, as the level of firm-specific human capital increases, the fraction of the fixed workforce also rises. In the simulation, the second effect outweighs the reduction in capacity, leading to an overall increase in fixed labor.

Next, we study how optimal choices of hoarded labor and the variance of the unhedged exchange rate change as a function of γ. Panels (b) and (c) of Figure 1 show that as γ increases, optimal hoarded labor increases while the chosen exchange-rate variance decreases. The intuition is simple: at the interior optimum (γ in the range $[\gamma_2, \gamma_3]$ as characterized in Proposition 2), more capacity and less hedging compete for scarce risk-bearing capability. At higher levels of γ, the default probability rises, increasing the shadow costs of capacity expansion and leading to higher levels of hedging.

Comparative statics. We further investigate how the relationship between hoarded labor and unhedged exchange-rate volatility changes under various parameter changes. Combining the two bottom panels of Figure 1, Figure 2 depicts in each panel optimal choices of hoarded labor on the x-axis and of unhedged exchange-rate volatility on the y-axis. A line corresponds to optimal choices of hoarded labor and hedging for firms with different levels of firm-specific human capital under otherwise fixed model parameters.

The following empirical predictions summarize these findings.

Testable Prediction 1. *In the cross section of firms, more hoarded labor is negatively associated with unhedged exchange-rate volatility.*

Testable Prediction 2. *All else equal, a firm with higher γ hoards more labor.*

Testable Prediction 3. *The relationship between hoarded labor and the unhedged exchange-rate variance weakens for a lower wage (lower w), lower demand volatility (lower σ), lower debt obligations (lower b), and lower hedge costs (lower k). In each case, depicted in the panels of Figure 2, the unconstrained optimum with no hedging is feasible for more firms, weakening the relationship of interest.*

3 Measuring Hoarded Labor from Short-Time Work (STW) Usage

Empirical analogs to (10) in the model are scarce, as they require data on temporary idle employee idleness associated with a given staffing decision. We exploit granular documentation on unused employee hours from firms' use of the job retention scheme short-time work (STW). Access to the scheme is usually highly restricted, but in certain periods—when the government temporarily relaxed eligibility by decree—a broad set of firms, including those with arguably normal operations, could use it. The core idea of the measure is to use average STW usage during the eased-access episode in 2020 for firms whose output in 2020 is similar to their output in 2019 and, thus, likely had similar overall labor input. A robustness with hoarded labor constructed from STW usage during the eased-access episode in 2009 yields similar results.

3.1 Institutional Context: Short-Time Work in Germany

STW is designed to protect viable jobs at overall healthy firms facing temporary external shocks (Giupponi and Landais, 2023; Cahuc, 2024). It allows firms to temporarily reduce working hours, with affected workers receiving benefits from the employment agency to replace most of the wage gap. The replacement rate is 60% (67% for employees with children). For example, a childless employee whose hours are reduced by 50% still receives 80% of their regular wage (50% regular wage plus 30% (= 60% × 50%) STW benefits). Firms pay STW benefits to employees upfront, and the employment agency later reimburses them.

Firms file an application for admission (*Anzeige*) to the STW scheme and, if approved, can choose monthly whether and to what extent to use STW. Typically, the maximum duration of STW is 12 months. Each month, firms submit detailed documentation (*Abrechnungslisten*) on STW usage at the employee level to obtain reimbursement. Payments from the employment agency are provisional until the end of the STW period, when a final examination (*Abschlussprüfung*) verifies whether eligibility criteria were met throughout the scheme's duration.

Access to STW is typically very restrictive, requiring firms to meet several eligibility criteria. First, the economic difficulties must be temporary and beyond the firm's control. Second, the firm must have exhausted all other measures, such as working-time accounts, and justify the necessity of STW for each job. Third, the shock must be sizeable, with at least a third of employees facing a reduction in hours of at least 10%.

3.2 STW during Eased-Access Episodes

Access restrictions to STW have been a policy lever and have been temporarily eased during crises. During the global financial crisis, the requirement that at least one-third of employees be affected was dropped (March 2, 2009, BGBl I. S. 430f), and the change extended until the end of 2011 (October 27, 2010, BGBl I. S. 1420f; December 20, 2011, BGBl I. S. 2854f). During the COVID-19 pandemic, only 10% of employees needed to be affected, and working-time accounts did not need to be exhausted first (March 13, 2020, BGBl I. S. 493f).

Usage across time. Unprecedented STW take-up—even in the second half of the year, when economic activity largely resumed—reflects minimal access restrictions to STW in 2020. Panel (a) of Figure 3 shows the share of firms using STW since 2009 among those matched to administrative employment data and with available revenue data in 2019 and 2020. Usage levels were high following the global financial crisis but reached unprecedented levels in the spring of 2020, with nearly 40% of firms in the sample in STW. The dotted lines indicate periods of eased access (2009-2011 and after March 2020). Strict lockdown measures in Germany ended in May 2020 and were not reimposed until mid-December 2020.

Industry-wide usage. This view is corroborated by high STW usage in 2020 in months and in industries in which industry-wide production was similar to production levels in 2019. In particular, we consider monthly industry-level revenue developments for the largest sectors in the sample. Panels (b)–(e) of Figure 3 show monthly industry-wide revenue (blue, left-hand scale) and STW usage (red, right-hand scale) for 2019 and 2020 in these industries. The figure illustrates that, although economic activity largely recovered in the second half of 2020, STW usage remained high. This pattern further supports the approach of using STW in the second half of 2020 to measure firm-specific levels of hoarded labor—something typically unobservable to the researcher.

Qualitative evidence. Qualitative survey evidence corroborates the view that access restrictions were temporarily lifted in 2020. An anonymized survey by proIAB among eight local employment agency branches on modified procedures in 2020, conducted in August 2022, reveals that mentioning "COVID" sufficed for admission to the STW scheme in the first month after March 2020, due to the need to handle the unprecedented number of applications operationally. By the summer of 2020, following a general directive, procedures had become slightly stricter. However, until the second lockdown, which started in mid-December 2020, a brief reference to COVID-19 typically sufficed without additional documentation. In 2021, pre-pandemic requirements for proof of eligibility were reinstated.

3.3 Construction of a Measure of Hoarded Labor

The empirical measure builds on monthly STW usage intensity and is constructed as follows. We define *Unused Fixed Labor* of firm i in month m as

$$\text{Unused Fixed Labor}_{im} := \frac{\text{Short-Time Work in Employee Equivalents}_{im}}{\text{Number of Employees}_{im}}. \tag{8}$$

Here, *Short-Time Work in Employee Equivalents*$_{im}$ is calculated by multiplying the number of short-time workers and the relative wage bill gap among short-time workers (for details on the relative wage bill gap, see Appendix B3). We define *STW Usage Intensity* for firm i, averaged across a set of months $\mathcal{M}$, as

$$\text{STW Usage Intensity}_{i,\mathcal{M}} := \sum_{m \in \mathcal{M}} \frac{1}{|\mathcal{M}|} \text{ Unused Fixed Labor}_{im}, \tag{9}$$

and, subsequently, *Hoarded Labor* for firm i as

$$\text{Hoarded Labor}_i := \text{STW Usage Intensity}_{i,\,\text{eased-access episode}}. \tag{10}$$

The baseline measure uses the eased-access episode from June to December 2020. As a robustness check, we construct a similar measure using data from 2009, averaging across the entire year.

We take several steps to reduce the influence of COVID-related labor underutilization on the measure. First, we use the year-on-year revenue change in 2020 as a proxy for output declines due to the COVID-19 shock and control for it throughout.[7] Second, and as detailed below, we substantially restrict the sample in three ways. We exclude data from the lockdown months up to and including May when constructing the measure; we restrict the analysis to firms whose 2020 revenue is not too atypical (year-on-year revenue change in the range of $[-20\%, 20\%]$); we require data on FX transaction income, naturally focussing the analysis on sectors such as the tradable-goods sector, which are less reliant on personal interactions.

4 Data

Our data is compiled from four main sources: establishment-level information on monthly STW receipt, matched employer-employee data, and commercially available firm financial information, which we enrich with novel information on firms' FX hedging extracted from hand-collected annual reports using text analysis.

Establishment-level information on monthly STW receipt. We use establishment-level data on monthly STW receipt from 2009 to 2020. Establishments that have been admitted to the STW

7 Year-on-year revenue changes reflect both price and quantity effects. If price effects were the main driver of revenue changes, however, we would expect a low correlation between year-on-year changes in revenue and material expenses, the latter proxying for input quantities. A correlation coefficient of 0.64 between revenue changes and material expenses validates revenue change as a proxy for output change.

program submit a detailed monthly application for reimbursement to the employment agency. The data we use are compiled for statistical purposes by the Statistics of the Federal Employment Agency ((*Statistik der Bundesagentur für Arbeit: Tabellen, Realisierte Kurzarbeit, Nürnberg, Oktober 2021, Daten mit einer Wartezeit von bis zu 5 Monaten (ohne Hochrechnung)*). The close link to the operational system on which the actual payment of benefits is based ensures high data reliability. The data provides monthly information on whether an establishment receives STW benefits, the number of short-time workers, the wage bill gap (i.e., the difference between the regular wage bill and the reduced wage bill, incorporating hours changes due to STW), and the hours gap in worker equivalents (in buckets; for details, see Appendix B3).

We convert the data to a monthly panel and merge it with the Establishment History Panel (Ganzer, Schmucker, Stegmaier, and Wolter, 2023), which contains information on all establishments in Germany with at least one employee liable to social security as of June 30 each year. This merge allows us to ensure basic consistency (see Appendix B1 for details) and to add location and industry information. We then aggregate the establishment-level data to the firm level, assigning to each firm the location and industry of its largest establishment.

Matched employer-employee data. Starting with the universe of German establishments that can be linked to firms (see Antoni, Koller, Laible, and Zimmermann (2018) for details on the confidential matching procedure), we observe employment histories based on German Social Security Records since 2008 for all individuals employed at some point at these establishments. The data stems from the Integrated Employment Biographies (IEB) database of the Institute for Employment Research. Specifically, it is based on employers' reports to the German social insurance system and includes the start and end date of each job, employees' earnings up to the censoring limit at the social security maximum earnings limit, an indicator for part-time or full-time employment, and information on education levels, occupation, and demographic characteristics.

We use standard procedures to create cross sections from the data originally stored in spell format. (Dauth and Eppelsheimer, 2020), transforming it into a monthly panel and then aggregating to obtain monthly employment at the firm level. Importantly, the detailed occupation information in the data allows us to calculate the year-end share of employees by occupation for each firm.

Firm-level financial information. Our main data on firm-level financial information comes from the commercial database Dafne, provided by Bureau van Dijk/ Creditreform. Dafne contains financial information on German firms since 2008 and is the underlying source for data on German firms in BvD's Orbis dataset (see, e.g., Jäger, Schoefer, and Heining (2021) and Moser, Saidi, Wirth, and Wolter (2021) for recent work with BvD data matched to German administrative data). Appendix B2 summarizes how we assemble and clean the firm-level financial data. Beyond annual balance-sheet and income-statement information at the unconsolidated level, we also observe the banks that firms have banking relationships with (*relationship banks*), which we match to banks in SNL Fundamentals by name (see Appendix B6 for details). We enrich bank balance-sheet information available in SNL Fundamentals with information obtained from text analysis of hand-collected annual reports of the universe of firms' relationship banks between 2010 and 2019.

Firm-level hedging information. Beyond separate items for (unhedged) FX transaction income that firms are required to report in their income statement (§277 Abs. 5 Nr. 2 HGB), they are also required to report on their use of derivatives and risk-management strategies in the appendices of their annual reports (§289 Abs. 2 Nr. 1 HGB). We conduct text analysis using the appendices of annual reports to extract keyword-based and AI-aided measures on FX derivatives usage and hedging strategies more broadly (for details, see Appendices B4 and B5).

Occupation information. In a final step, we rely on occupation-level information on hiring difficulties and the prevalence of vocational training. Information on hiring difficulties comes from a bi-annual classification by the German Federal Employment Agency that compiles a list of so-called shortage occupations (see Section 7.1 for details). We use the classification as of December 2019.[8] Information on the prevalence of vocational training comes from the 2019 wave of the Occupational Panel (see Grienberger, Janser, and Lehmer (2023) for details), which is based on the universe of German Social Security Records and the Federal Employment Agency's occupational expert database (*Berufenet*).

Sample selection. From the starting point of all German firms that report an income statement, specifically revenue, at the unconsolidated level in 2019 and 2020 and satisfy basic data-consistency

8 See `https://statistik.arbeitsagentur.de/SiteGlobals/Forms/Suche/Einzelheftsuche_Formular.html?nn=20626&topic_f=fk-engpassanalyse`.

requirements (similar to (Kalemli-Ozcan, Sorensen, Villegas-Sanchez, Volosovych, and Yesiltas, 2015), see Appendix B2 for details, 16,323 firms)[9], we select the following sample of firms. We match these firms to the confidential employment data described above, aggregated to the firm level, achieving a successful match rate of 71%. We restrict attention to firms with at most 20 establishments (11,482 firms) and further to those for which employment information from annual reports roughly coincides with the aggregated establishment-level employment information at the IAB (within a tolerance of -20% to +100%; 10,071 firms). This approach ensures that firms in the sample primarily have employment in Germany. Following standard data-cleaning practices in the literature, we exclude regulated utilities (sections D and E of the Classification of Economic Activities (WZ 2008)), financial firms (section K), and firms in public services (section O), resulting in 9,145 firms. For the full sample, we restrict attention to firms with year-on-year revenue changes in 2020 between -20% and +20%, resulting in 6,913 firms. For the sample of firms with FX data, we further focus on those that report FX transaction income in at least two years between 2010 and 2019 and for which information on their export share is available, resulting in 2,352 firms.

Summary statistics. Table 1 presents the summary statistics for the full sample in Panel (a) and for the subset of firms with FX data in Panel (b). Both datasets include core financial information and workforce characteristics, whereas information on exports, FX-induced CF volatility, and hedging is only available for the subset.

Firms with FX data are, on average, larger than firms in the full sample (450 vs. 350 employees) and likely contain a higher share of *Hidden Champions* (Simon, 1996): highly specialized SMEs that are technology leaders in a global—often produce-to-order— niche markets with significant export activity.[10] On average, firms with FX data have higher value added per employee (0.17 million EUR vs. 0.13 million EUR), which is also reflected in higher average daily wages (52.80 EUR vs. 45.71 EUR). This selection toward higher-paying firms corresponds to a shift in industry composition (cf. Panel (a) of Appendix Figure C.4), with the share of manufacturing firms doubling (62% vs. 32%). The largest sectors in the FX sample are manufacturing, trade, information and communication,

9 The number is not larger, because firms that exceed not more than one of three size thresholds (12 mio revenues, 6 mio assets, and 50 employees) need not publish an income statement in Germany.

10 The increase (37% vs. 29%) in firms from southern Germany, a region home to many such firms, aligns with this.

and professional, scientific, and technical activities. This shift in sectoral composition implies that we focus on sectors less dependent on personal interactions and, thus, less affected by the pandemic to begin with, further alleviating concerns about lockdowns biasing the hoarding measure.

5 Who Hoards?

We start by presenting evidence that STW usage in our sample reflects more than COVID-related labor underutilization. We then provide descriptive statistics on the characteristics of firms that hoard labor and test our measure against the intuition that labor hoarding strengthens the comovement of profitability with demand.

5.1 Beyond the COVID-19 Shock

As apparent in the raw data, STW was widely used even among firms without a revenue drop in 2020. Figure 4 links STW usage in 2020 to year-on-year revenue changes, showing binned scatterplots of STW usage intensity against revenue changes. For firms that experienced a revenue drop (cf. Panel (c) of Appendix Figure C.4), STW usage intensity is strongly associated with revenue changes. For firms with positive revenue growth, however, this association disappears, yet STW usage intensity remains at approximately 1-2% on average, regardless of the level of revenue growth. A similar pattern emerges for STW usage (binary) in Panel (b) of Figure 4.

To underscore the uniqueness of the eased-access episode in 2020, we replicate Figure 4 using pooled data from years with regular access to STW as a placebo test. Panel (a) of Appendix Figure C.5 shows binned scatterplots of annual STW usage intensity against year-on-year revenue changes, pooled across firm-year observations between 2012 and 2019. The scale is the same as in the scatterplots for 2020. The figure indicates minimal STW usage during periods with regular access restrictions, with only a modest correlation between STW usage and revenue declines.

Even when focusing on firms with similar revenue in 2020 compared with 2019, the measure could still be biased upward or downward if the total number of employees was lower or higher in 2020 than in 2019. For instance, firms may have hired additional workers in early 2020 in anticipation of growth or have laid off workers despite STW. However, Appendix Figure C.6, depicting monthly industry-wide employment developments for the four largest industries in the sample, reveals no discernible aggregate employment change during the months upon which the measure is based (shaded area).

5.2 Firm Characteristics

We use the new measure to shed light on the characteristics of firms that hoard labor. Appendix Figure C.7 plots coefficients from a regression of hoarded labor on various firm characteristics, comparing firms within the same industry and region and controlling for revenue changes.

Firms with higher levels of hoarded labor tend to be somewhat smaller, consistent with the idea that smaller firms have less access to internal labor markets than large firms Cestone, Fumagalli, Kramarz, and Pica (2024). Labor hoarding is not statistically significantly related to export share, leverage, or cash holdings, but labor-hoarding firms display slightly lower capital intensity, measured by value added per employee. Their return on assets is lower, which likely reflects residual negative selection into STW (as in Giupponi and Landais (2023); Kagerl (2024) despite the relaxed access conditions. In the analyses that follow, we account for this by controlling for return on assets and value added per employee in robustness checks.

5.3 Larger Comovements of Cash Flow with Demand for Labor-Hoarding Firms

Whereas labor hoarding generates idle labor and higher wage costs during periods of low demand, it also enables higher production when firms operate at full capacity during periods of high demand. We test this "first stage" of the mechanism in a firm-year panel, identifying labor-hoarding firms, invariantly across time, based on our constructed measure. We find that the comovement of year-on-year changes in profitability with industry-wide upturns and downturns is indeed stronger for labor-hoarding firms than for their non-labor-hoarding counterparts.

Empirical design. To empirically explore this upside potential of labor hoarding, we examine the difference in the comovement of profitability changes with demand changes between labor-hoarding and non-labor-hoarding firms and expect to find a stronger correlation for the former. Specifically, we estimate the following regression for year t and firm i in industry $s(i)$:

$$\Delta Y_{it} = \beta \, \text{Labor Hoarding}_i \times \Delta \text{Demand}_{s(i)t} + \alpha_i + \alpha_{s(i)t} + \varepsilon_{it}, \tag{R1}$$

where α_i and $\alpha_{s(i)t}$ denote firm-level and industry-by-year-level fixed effets. The coefficient of interest is β. *Labor Hoarding*$_i$ is a firm-level binary variable that takes the value of 1 if a firm engages in labor hoarding. The outcome of interest, Y_{it}, is annual profitability. We proxy year-on-year changes in demand at the industry level by using changes in the ifo Business Climate Index (6-month-ahead expectations) for each industry between the Marches of consecutive years. The ifo Business Climate Index, provided by the ifo Institute, is a widely regarded survey-based indicator of the German economy, calculated from monthly responses of more than 10,000 companies (see Sauer, Schasching, and Wohlrabe (2023) for details).

Results. Table 2 shows the results of regressions of the form (R1), using return on assets (ROA) in columns 1-3 and CF in columns 4-6 as a measure for firm-level profitability. Columns 1 and 4 do not include firm fixed effects but instead include *Labor Hoarding* separately. We add firm fixed effects in columns 2 and 5 and industry-by-region-by-time fixed effects in columns 3 and 6 to account, as much as possible, for potential mismeasurement of demand fluctuations. The estimates confirm a stronger comovement of changes in profitability with changes in industry-wide demand for labor-hoarding firms.

Robustness. As a robustness check, we zoom in on the manufacturing sector and confirm the result by proxying demand fluctuations by changes in orders at more granularly defined industry levels (available only for the manufacturing sector). Panel (b) of Appendix Table D.1 shows the firm-year panel used for Table 2 contains more upturns than downturns (78% vs. 22%). To address this imbalance and provide an alternative measure of demand fluctuations, we focus on the manufacturing sector, where a volume-based normalized index of orders is available at a monthly frequency. In the resulting firm-year panel, reduced to one-quarter of the observations, 49% of observations correspond to upturns (bottom of Panel (b) of Appendix Table D.1). Panel (a) of Appendix Table D.1 corroborates the previous findings using this alternative proxy for demand fluctuations.

6 A Link between Labor Hoarding and Risk Management

Next, we link firms' labor hoarding to their risk management. Whereas labor-hoarding firms exhibit larger comovements of their cash flows with industry-level upturns and downturns (as shown in the previous section), increased labor hoarding is not associated with higher overall CF volatility. Instead, hoarded labor is negatively correlated with unhedged foreign-exchange-related risk, one risk-adjustment margin for these largely high-tech manufacturing SMEs.

6.1 No association with larger overall CF volatility

To understand if labor-hoarding firms are riskier overall, we examine their total CF volatility. Specifically, we estimate cross-sectional regressions of the form

$$\text{CF Volatility}_i = \beta\,\text{Hoarded Labor}_i + \theta'\mathbf{X}_i + \varepsilon_i, \tag{R2}$$

where *Hoarded Labor*$_i$ for firm i is defined as in the previous section, and $\mathbf{X}_i$ is a vector of control variables based on 2019 and fixed-effect dummies (industry by region). *CF Volatility* is defined as the standard deviation of CF scaled by revenue based on annual data from 2010 to 2019.

Panel (a) of Table 3 shows that firms with more hoarded labor do not exhibit higher total CF volatility. Column 1 uses a binary indicator, *Labor Hoarding*, whereas the remaining columns use the continuous measure *Hoarded Labor* on the left-hand side. Value added per employee and ROA are included in columns 3 and 4 to control for differences in capital intensity and productivity, yet there is still no statistically significant correlation with hoarded labor. Focusing on FX-induced CF volatility shrinks the sample by about two-thirds due to data availability (cf. Panel (b) vs. Panel (a) of Table 1). Among firms with FX data, hoarded labor is also not significantly correlated with total CF volatility, but it is significantly correlated with FX-induced CF volatility (column 5 vs. column 6).

6.2 One margin of adjustment: Unhedged Foreign Exchange (FX) Risk

We construct two measures of FX-induced CF volatility from the accounting variables FX gains and FX losses following Adams and Verdelhan (2022).[11] We calculate net FX gains scaled by revenue in year t,

$$\text{Net FX Gains}_t := \left(\text{FX Gains}_t - \text{FX Losses}_t\right) / \text{Revenue}_t, \tag{11}$$

and define two firm-level measures of FX-induced CF volatility:

$$\begin{aligned} \text{sd net gains} &:= \text{sd}\Big\{\text{FX Net Gains}_{2010}, \ldots, \text{FX Net Gains}_{2019}\Big\} \cdot 100 \\ \text{max net loss} &:= -\min\Big\{\min\left\{\text{FX Net Gains}_{2010}, \ldots, \text{FX Net Gains}_{2019}\right\}, 0\Big\} \cdot 100. \end{aligned} \tag{12}$$

Both measures are winsorized at the 1% and 99% level to remove outliers. The first measure provides an intuitive starting point for measuring volatility. The second measure captures the largest loss induced by net FX positions and aligns more closely with heightened default risk from exchange-rate movements, the ultimate concern for risk-averse firms. Thus, it more closely maps to the constraint in the model.

The following example provides an intuitive illustration of what *FX Gains* and *FX Losses* capture. Consider a firm that produces in Europe and exports to the US. The firm invoices and ships goods on March 1 at a price of $1 mil, with payment due three months later on June 1. At the time of invoicing, $1 is worth 1.05 EUR, so the firm records 1/1.05 mil EUR on March 1. Suppose the exchange rate moved to 1.15 EUR per USD by the settlement date. At the settlement date, the firm receives 1/1.15 mil EUR and records the change in value as an FX loss of (1/1.15 - 1/1.05) mil EUR = 80,000 EUR. If the firm conducts multiple such transactions throughout the year, it collects the corresponding revaluations in the variables FX losses and FX gains.

Appendix Table D.3 corroborates a negative correlation between hoarded labor and FX-induced CF volatility under both measures and varying sets of controls. Columns 3-4 add value added per employee to control for differences in capital intensity or labor productivity. This matters for the relationship of interest if more capital-intensive firms are less likely to use STW but more likely to export globally and be exposed to foreign currency, primarily USD, invoicing. We also use ROA as a proxy for profitability in columns 5-6. The negative correlation between hoarded labor and FX-induced CF volatility remains robust across specifications.

11 They use the accounting variables for publicly traded firms, and we demonstrate the approach's applicability also to private firms.

Discussion. The accounting variables *FX Gains* and *FX Losses* capture FX risk after hedging, thereby aligning with the model framework. To illustrate, suppose the firm in the earlier example purchases a forward contract with a notional of $1 mil at a forward rate equal to the spot rate on March 1. The firm is perfectly hedged in this case, and no revaluation effect is expected. When the forward contract matures on June 1, it has the same value as the spot rate. Hence, the change in value of the hedged item, (1/1.05 - 1/1.15) mil EUR, is exactly offset by the change in value of the hedge, (1/1.15 - 1/1.05) mil EUR. Under the German Commercial Code, a firm that uses hedge accounting (specifically fair-value hedges) can choose between two accounting methods. With the freezing method (*Einfrierungsmethode*), the hedge fully neutralizes the FX transaction risk. With the pass-through method (*Durchbuchungsmethode*), the FX loss from the value change of the hedged item is offset by an FX gain of the same amount from the value change of the hedge. Although these methods imply different interpretations of the variables *FX Gains* and *FX Losses* separately, both result in the same value (net of hedging) for net FX gains.

Appendix Figure C.8 illustrates the relevance of FX risk for firms in the sample. Specifically, it shows the distribution of net FX gains in three consecutive years. In 2017, over 10% of firms experienced unhedged FX gains or losses exceeding 10% of their annual profits. FX-induced CF volatility amounted to, on average, around 1/14 (= 4.47/0.32) of total CF volatility (see Panel (b) of Table 1). Another indication of the importance of FX risk for exporting SMEs is its prominence in the portfolios of local relationship banks. For many local banks, FX derivatives are the most important type of derivative sold to commercial clients, with outstanding amounts surpassing 15 billion EUR in 2016 (see Panels (d) and (e) of Appendix Figure C.8).[12]

The accounting variables *FX Gains* and *FX Losses* serve as proxies for FX risk but likely underestimate the full extent of exchange-rate exposure. The variables primarily capture exchange-rate movements between invoicing and payment dates. Because invoicing typically occurs when the goods are shipped, price changes between the point of sale and invoicing are not accounted for. Similarly, for long-term contracts – such as those involving large machinery – interim payments are common, meaning a significant portion of the payment may already have been made when the goods

12 Foreign-currency financing is unlikely to be a major concern for these firms, because they tend to be relatively small and privately held. Given Europe's bank-based financing system, SMEs are unlikely to rely considerably on bond markets for funding. Regarding bank loans, data from the BIS location banking statistics show only 1.5% of total bank claims or liabilities in Germany are denominated in currencies other than euro.

are shipped, further limiting the extent to which *FX Gains* and *FX Losses* fully capture overall FX risk.[13]

6.3 Heterogeity across Firm Characteristics

The negative correlation between hoarded labor and unhedged FX risk aligns with the first model prediction. To test the third model prediction, we examine heterogeneity of the correlation across firm characteristics. Columns 1 and 2 of Appendix Table D.2 show the correlation is weaker for firms with a low labor share, a proxy for the wage w in the model. For the subset of manufacturing firms, we use granular industry-level data from the Federal Statistical Office of Germany (tables 42151-0002) to proxy for demand volatility by calculating the volatility of a value index of monthly incoming orders between 2010 and 2020. The results in columns 3 and 4, based on less than half of the sample, suggest a weaker effect in industries with low order volatility, consistent with the model. We find no difference in the effect between firms with high and low leverage (columns 5 and 6).

The clear attenuation of the effect for firms with more than three relationship banks (columns 7 and 8 of Appendix Table D.2) is consistent with the model's comparative statics for lower hedge costs but also points toward unobserved firm characteristics as a potential source of bias in the OLS estimates. A larger number of relationship banks may proxy for more sophisticated risk-management practices, which in turn could confound the OLS estimates, because firms with more advanced risk management are likely to hedge price risks more effectively and may also have organizational structures that reduce employee idleness. For instance, some firms employ staff dedicated to so-called "staff level optimization," designing strategies to rotate employees across divisions to minimize downtime. Risk-management sophistication would then bias the OLS estimates towards zero.

13 In practice, a German firm exporting to the US usually has a US subsidiary. However, FX gains and losses typically still accrue to the parent company if the subsidiary only distributes, rather than produces. In this case, the subsidiary buys goods from the parent company at arm's length prices denominated in USD, transferring the FX risk to the parent company. Given that the firms in the sample have most of their employees in Germany, one can reasonably assume their foreign subsidiaries are only involved in distribution, not production.

7 Firm-Specific Human Capital as a Driver for Hoarding

The negative correlation between hoarded labor and unhedged FX risk may be biased from various sources of endogeneity, such as unobserved firm characteristics like risk-management sophistication. Ideally, we would observe identical firms that face the same stochastic demand over time and choose the constrained optimal level of hoarded labor. If, for some exogenous reason and holding everything else constant, one firm chooses a higher staffing level, our hypothesized mechanism implies that, while this firm may benefit more in periods of high demand, it reduces its unhedged FX exposure. Guided by the model, we construct instruments based on the difficulty of onboarding employees in certain occupations, proxying for differences in firm-specific human capital (FSHC).

7.1 Identification Strategy

Through the lens of the model, firm-specific human capital is a suitable instrument for hoarded labor. In the model, firms require two complementary types of workers for production: fixed and variable labor, and they exogenously differ in their dependence on fixed labor, which we call *firm-specific human capital*. When firms only maximize expected profits, the level of firm-specific human capital shapes their decision on how much fixed labor, and hence how much hoarded labor, to hold, but has no bearing on the decision of how much exchange-rate risk to assume (Lemma 1). FSHC affects both hoarded labor *and* hedging only when the constraint binds, and the hypothesized trade-off has bite. The empirical finding that hoarded labor is not correlated with total cash flow volatility lends some credibility to the presence of a binding constraint in our empirical setup.

We construct two shift-share-type instruments (Goldsmith-Pinkham, Sorkin, and Swift, 2020) using firms' occupational compositions as shares, and occupations with lengthy hiring times (for shortage occupation-based FSHC) or lengthy training periods (for vocational training-based FSHC) as shocks, as detailed below. We then estimate the following 2SLS specification.

$$\begin{aligned} \text{Hoarded Labor}_i &= \alpha \ \text{FSHC}_i + \theta' \mathbf{X}_i + \eta_i \\ \text{FX-Induced CF Volatility}_i &= \beta \, \widehat{\text{Hoarded Labor}}_i + \theta' \mathbf{X}_i + \varepsilon_i, \end{aligned} \tag{R3}$$

with $\mathbf{X}_i$ a vector of control variables based on 2019 and fixed-effect dummies (industry by region).

Occupation composition. Identification relies on the idea that firms' technologies are fixed, at least over some time window, and that technology determines each firm's occupational composition (as in Crouzet, He, Lyonnet, and Ma (2025)). Leveraging detailed occupation information available over time in the German matched employer-employee data, we compute year-end shares of employees by occupation for each firm. Following standard practice in the literature (see, e.g., Grienberger, Janser, and Lehmer (2023)), we define an *occupation* at the level of the occupational group (three-digit level) combined with the requirement level (fifth digit). The requirement level distinguishes between unskilled/semiskilled workers, skilled workers, specialists, and experts.

To shed some light on the occupational composition, we provide summary statistics for the largest occupations in the sample in Table 4. Occupations in machine-building and -operating at the specialist level are the largest occupation group, with an average share of 9.8% in 2019 (10% in 2018) among firms that have at least one employee in this occupation (1,597 firms in 2019). This masks substantial heterogeneity in the relevance of these occupations, with a share of 6.03% in the median firm and 24.57% at the 90th percentile. The picture remains very similar for 2018, already pointing toward a high degree of stability in firms' occupational compositions, which we test more formally later. The last two columns report, per occupation, the share of employees with vocational training (from the occupation panel) and an indicator for whether the occupation is classified as a shortage occupation, which we discuss in the following.

Occupations with lenghty hiring time. To identify occupations in which onboarding times exceed the demand forecast horizon because of hiring difficulties, we draw on a classification of certain occupations as *shortage occupations*, as detailed below. We define for firm i

$$\text{FSHC (Shortage Occup-Based)}_i = \sum_j \text{Share Occup}_{ij} \cdot \mathbf{1}(\text{Occup j is Shortage Occup in Dec 2019}).$$

The German Federal Employment Agency compiles, every six months, a list of these so-called shortage occupations (*Engpassberufe*) in which firms have an exceptionally hard time finding employees. The definition of shortage occupations seeks to identify structural problems in filling positions within specific occupations based on three indicators. First, the average vacancy duration in the occupation must be at least 30% longer than the overall average. Second, the ratio of unemployed to job postings must be smaller than 2:1 for skilled workers and specialists, and 4:1 for experts. Third, the unemployment rate in the occupation must be below 3%. If all three criteria are met, and an expert confirms the classification, the occupation is designated as a shortage occupation. These criteria are designed to minimize the influence of hiring challenges specific to individual firms, such as poor working conditions or limited mobility among the unemployed. We enrich federal-level shortage classification (per requirement level, aggregated from the four-digit level to occupational groups) with an analogous classification for occupations at the regional (*Bundesland*) level.

The classification captures hiring difficulties for firms within a given occupation but may also reflect factors other than the firm-specificity of the required knowledge. First, these occupations likely pay below-equilibrium wages. Over longer horizons, wage levels would be expected to adjust, attracting more workers into these occupations and alleviating the shortage. At least in the short run, however, such adjustments—especially when they involve young people choosing career paths—are likely to be limited, so that the observed hiring difficulties reflect genuine shortages. Second, shortage occupations may themselves partly reflect labor hoarding by other firms, which we cannot detect prior to the eased-access episode in 2020. We therefore complement our analysis with an additional instrument, described in the following.

Occupations with lenghty training time. To identify occupations in which onboarding times exceed the demand forecast horizon due to extended training times, we alternatively draw on the occupation-specific importance of *vocational training*. Firms may also be unable to hire upon demand shocks because some occupations require firm-specific training that takes longer to acquire. The second instrument emphasizes this aspect and uses the importance of vocational training by occupation. Specifically, we define for firm i

$$\text{FSHC (Voc Training-Based)}_i = \sum_j \text{Share Occup}_{ij} \cdot (\text{Aggreg Share w/ Voc Training in 2019})_j.$$

Germany's vocational training system (Dustmann and Schönberg, 2012) is built on training that takes place within firms rather than only at vocational schools. Employees with vocational training have completed firm-based on-the-job training as part of apprenticeship schemes that typically last around three years and are supplemented by classes at vocational schools once or twice a week.

During firm-based vocational training, firms have an incentive to invest in developing firm-specific knowledge and skills, motivated by the prospect of hiring their apprentices after training. Survey evidence shows that firms are willing to offer employment contracts to apprentices in about 90% of cases (Mohr, 2015).

To alleviate the concern that investment in vocational training may itself be a source of risk, for example, due to capital expenditures for training facilities, we do not use the firm-level share of workers with vocational training. Instead, we rely on the relevance of vocational training per occupation, as measured in the Occupational Panel.

Instrument validity. Instrument validity hinges on the standard requirements of relevance and the exclusion restriction. Regarding relevance, we expect a higher level of FSHC to be associated with a higher level of hoarded labor. The bottom of each panel in Table 5 reports the estimated first-stage coefficients for the shortage occupation-based instrument in Panel (a) and the vocational training-based instrument in Panel (b). Both coefficients are positive, consistent with the model. The magnitude of the coefficient in Panel (a), for example, implies a 100-basis-point increase in the share of employees in shortage occupations is associated with a 26-basis-point higher fraction of the workforce that is temporarily idle on average. The resulting first-stage F-statistics (Kleibergen–Paap Wald statistics; see Andrews, Sock, and Sun (2023)) are 23.04 and 11.07, respectively, and thus exceed the Stock and Yogo (2005) threshold for weak instruments.

The exclusion restriction requires that the instrument be uncorrelated with unobserved variables that affect the relationship of interest in (R3). Because our measure of hoarded labor is confined to eased-access episodes and our measure of FX-induced CF risk requires multiple years, the analysis is restricted to a cross-section of firms, and firm FEs are thus infeasible. However, we always compare firms within the same industry and region and control for firm size and exposure to the COVID-19 shock (revenue change).

To assess the plausibility of the exclusion restriction, Appendix Table D.4 splits firms into those with above-median and below-median FSHC, separately for each instrument. For the shortage occupation-based instrument (Panel (a)), and focusing for now on the top two subpanels, firms in the two groups are indistinguishable in terms of size in two of the three measures (assets, revenue). The same holds for leverage (at the 5% level), cash holdings, ROA, value added per employee, as well as the average age and wage of their employees. Employees at firms with an above-median share of employees in shortage occupations have statistically significantly higher tenure, consistent with intuition. For the vocational-training-based measure (Panel (b)), again focusing on the top two subpanels, the two groups of firms are indistinguishable in size by any measure. The same is true (at the 5% level) for ROA and value added per employee. They do, however, differ in leverage and cash holdings, as well as in employee characteristics in terms of age, wage, and tenure.

Further discussion. We further discuss three specific concerns regarding the exclusion restriction. First, the exclusion restriction would be violated if firms' exposure to global markets—and thus their cash flow volatility due to exchange-rate movements—shaped their technology and, as a result, their demand for employees across occupations. We address this concern in two ways. First, we control for the export share in all regressions. Second, we show that firms' occupational compositions are highly stable over time and do not vary systematically with the export share. To this end, we exploit the panel dimension of our data and identify, for each firm, its three largest occupational groups in 2019. We then compute, for the previous four years, the year-end shares of employees in these occupations. Appendix Table D.5 shows that these shares are highly stable over time. In particular, in the specification including lagged export share—which reduces the sample due to limited export-share information over time—90% of the variation is explained by firm fixed effects, while year fixed effects have little explanatory power. In the specification with the most granular fixed effects, the shares are not correlated with the lagged export share.

A second source of concern is that firms may still differ in terms of unobserved risk-management sophistication. Although we do not find statistically significant size differences using size as one proxy for sophistication, we also examine firms' banking structures (bottom subpanels in Panel (a) and (b) of Appendix Table D.4) as an additional proxy. Firms with a high level of FSHC according to both measures have, on average, more banking relationships. However, when looking at the composition of relationship banks, this difference is driven by a greater number of local banks (commercial and savings banks), whereas the two groups do not differ in a statistically significant way in their links to the major German banks with the most derivative offerings (*Deutsche Bank, Commerzbank, UniCredit*). This is also reflected in a statistically insignificant difference in access to hedging, proxied by the probability of using FX derivatives in 2019.

Third, one may worry that firms differ in their propensity to outsource (as in Bergeaud, Malgouyres, Mazet-Sonilhac, and Signorelli (2025)). To alleviate this concern, we additionally control for ROA and value added per employee as proxies for productivity in Panel (a) of Appendix Table D.6 and find that the key result remains unchanged.

7.2 Impact of Labor Hoarding on Unhedged FX Risk

Figure 5 illustrates the instrumental variable (IV) design, depicting the first stages (Panels (a) and (c)) and the second stages (Panels (b) and (d)) for both instruments. The visualization already points toward a causal effect of labor hoarding on the unhedged FX risk assumed by firms, which we test more formally in the following.

For the shortage occupation-based instrument, Panel (a) of Table 5 presents the baseline 2SLS estimates (columns 3 and 4) alongside the OLS (columns 1 and 2) and reduced-form estimates (columns 5 and 6). The magnitude of the 2SLS estimates suggests that a one-standard-deviation increase in hoarded labor reduces FX-induced CF volatility by 0.62 standard deviations ($= (7.192 \times 0.053)/0.615$). The estimates for both measures of FX-induced CF volatility are similar in size (0.62 vs. 0.68 standard deviations), and the strong statistical significance of the reduced-form estimates further supports a causal link.

For the vocational-training-based instrument, Panel (b) of Table 5 shows the analogous results. The magnitude of the 2SLS estimates is more than twice as large, which is likely related to the substantially weaker instrument (F-statistic of 11.07 vs. 23.04). However, the presence of effects across instruments that capture different types of frictions reinforces the evidence for a causal effect. The results change little when both instruments are included simultaneously in Appendix Table D.7. The overidentification tests in the baseline specifications all pass at the 5%-level.

Discussion. Following Jiang (2017), we reconcile the increase in magnitude of the 2SLS estimates compared to the OLS estimates with the bias anticipated in the OLS. The two primary endogeneity concerns in the OLS are omitted-variable bias and reverse causality. Omitted-variable bias, such as unobserved sophistication in risk management, would bias the OLS estimates toward zero, because firms with more advanced risk-management practices likely experience both reduced employee downtime through improved organization and better financial hedging. Reverse causality, such as firms with lower FX risk portfolios having greater flexibility to hoard labor, would instead bias the OLS estimates toward zero. The relative magnitudes of the OLS and IV estimates suggest that omitted-variable bias dominates reverse-causality concerns. This interpretation is consistent with the observed weakening of the effect in the OLS for firms with more than three relationship banks, proxying for risk-management sophistication (cf. Appendix Table D.2).

Second, we discuss potential amplification effects. Jiang (2017) argues that a design may suffer from a small partial R^2 of the excluded instruments in explaining variation in the endogenous variable, which can create a weak-instrument problem even when the first-stage F-statistic is sufficiently large.[14] In such a scenario, even a small second-order direct effect of the instrument on the outcome can lead to inflated estimates. In Appendix Table D.6, for the shortage occupation-based instrument, we include ROA and value added per employee as additional controls and examine partial R^2 across specifications. The bottom rows of Panel (a) report the partial R^2 of the excluded instruments for explaining variation in hoarded labor. The 2SLS estimates are indeed somewhat smaller -6.984 (-13.036) in column 3 (column 4) versus -7.192 (-13.069) in column 1 (column 2), while the partial R^2 increases by an order of magnitude (0.022 vs. 0.009). Although the existence of the effect appears robust, the finding does not fully mitigate concerns about slightly inflated 2SLS estimates.

Robustness. We conduct two further robustness tests. First, in Appendix Table D.8, we repeat the analysis using an analogously constructed measure of hoarded labor based on the 2009 eased-access episode. We control for exposure to the Global Financial Crisis through the year-on-year change in revenue in 2009, as well as for firm size and export share. This exercise also helps to alleviate measurement concerns, since hoarded labor measured in 2009 predates the window used to compute FX-induced CF volatility (2010-2019). The OLS estimates remain similar in magnitude to our baseline results. In columns 3 and 4, we instrument hoarded labor with the share of employees with vocational training in 2008. Because a change in the occupational classification in 2011 makes it infeasible to reconstruct our earlier instruments for 2008, the vocational-training share serves as a close proxy for the vocational training-based instrument. The instrument yields positive first-stage

14 In some cases, however, a small partial R^2 may not indicate a weak-instrument problem, for example, when the variance in the first stage is very large per se and the IV is nonetheless valid.

coefficients but small first-stage F-statistics. The 2SLS estimates are negative and statistically significant, and Anderson-Rubin χ^2 p-values are small, supporting the existence of an effect.

In a second robustness test, we replicate the analysis using a subset of firms for which export-destination data confirm exports to outside the euro area, indicating a higher likelihood of non-euro-denominated transactions.[15] We classify firms based on text information on their export destinations provided by BvD. Following Gopinath and Itskhoki (2022), we assume exports within Europe (excluding the UK) are denominated in euro, while the USD is the dominant currency for exports outside Europe. Panel (b) of Appendix Table D.6 shows that the result persists even in this subsample, which reduces the sample size by more than half. Moreover, the fact that more than 80% of firms with export-destination data export outside the euro area (see Table 1) suggests that such exports play a major role in the unrestricted sample as well.

8 Hedging Strategies

Finally, we examine the mechanism in more detail by assessing whether cash holdings mediate the effect and by analyzing the types of FX hedging strategies that firms employ.

Role of cash. Cash holdings represent another important precautionary buffer for firms. To explore whether high cash holdings mediate the effect, we divide the sample into firms with above-median and below-median cash holdings in 2019. The first two columns of Table 6 report the heterogeneity analysis along this dimension; however, the first-stage F-statistics for the interaction term fall below 10. The point estimates are positive—which is consistent with the idea that high cash holdings may partially mediate the effect—but not statistically significant.

Use of FX derivatives. Since data on non-financial firms' derivatives usage are scarce, we first present two sets of stylized facts from a keyword-based measure constructed from hand-collected annual reports in Appendix Table D.9. A firm is classified as a derivatives user if keywords such as "FX forward" or "derivative" appear in the appendix of its annual report (see Appendix B4 for

15 According to the data in Boz, Casas, Georgiadis, Gopinath, Le Mezo, Mehl, and Nguyen (2022) across all export destinations, around 75% of German exports in 2019 were euro-denominated and around 20% were USD-denominated. This pattern is consistent with the assumption that the USD is the dominant global invoicing currency, given that roughly 70% of German exports are within Europe and are likely euro-denominated. We classify a firm as exporting outside the euro area if it lists at least one export destination outside Europe.

details). Approximately 25% of firms in the sample are identified as FX-derivatives users. These firms are larger across all size measures (Panel (a) of Appendix Table D.9), with the median user being about twice as large as the median non-user. Non-users tend to hold more liquidity, are slightly more profitable, and have an average export share that is 10 percentage points lower than that of users.

Second, we find suggestive evidence that FX-derivatives usage is targeted more toward exports than imports. Panels (b) and (c) in Appendix Table D.9 examines the relationship between FX-induced CF volatility and the export share and the import share. The export share is strongly correlated with FX-induced CF volatility but less so for derivatives users, as indicated by the negative interaction coefficient in column 1 of Panel (b). Due to data availability, the sample shrinks substantially when the import share is included as a control (column 2). The result persists when we restrict the sample to firms with available export-destination data that export outside the euro area (columns 6 and 7). The result persists when focusing on firms with available export-destination data that export to outside the euro area (columns 6 and 7). However, the weakening of the link for users is only present between exports and FX-induced CF volatility and disappears for imports in Panel (c).

We then examine heterogeneity in our main result based on whether firms use FX derivatives or not. Columns 3 and 4 of Table 6 present the 2SLS estimates using the shortage occupation-based instrument, allowing the effect to differ by FX-derivatives usage. Although not both beyond 10, the first-stage F-statistics for the main effect and interaction effect are sizeable. The effect is indeed primarily driven by firms that use FX derivatives.

Operational vs. financial hedging strategies. In addition to financial hedges, firms may also employ operational hedging strategies. However, identifying the use of varying and potentially highly individualized operational hedging strategies through a keyword-based approach is challenging. To address this issue, we apply AI to analyze the risk-management sections of appendices in annual reports to determine whether a firm actively manages FX risk (see Appendix B5 for details). According to this AI-based classification, 42% of firms actively manage their FX risk, as shown in Panel (b) of Table 1.

Heterogeneity based on this measure suggests that the previous results are primarily driven by firms that actively manage FX risk. Columns 5 and 6 of Table 6 report the 2SLS estimates using the shortage-occupation-based instrument, allowing for heterogeneity based on the AI-generated classification. With the largest first-stage F-statistics for the main and interaction effects among the heterogeneity analyses so far, the 2SLS estimates show that the effect largely stems from firms that actively manage their FX risk. This finding underscores the importance of active FX hedging—be it through operational and financial hedging strategies—as a risk-management tool for these firms.

To qualitatively understand which operational hedging strategies firms employ, we manually classify the strategies mentioned for a random subset of firms. The classification is based on the five sentences in the annual reports that the AI identified as key to its classification. We focus on firms that the AI flagged as actively managing FX risk, examining 175 firms from a random sample of 500. Figure 6 presents the results of the manual classification of hedging strategies. The most common strategy is the use of financial FX hedging instruments (42%), followed by invoicing in euro (15%), natural hedging (11%), and participation in group-level FX hedging (11%). Invoicing in euro masks two different scenarios: either FX risk is minimal because exports are primarily directed to euro-area countries, or firms choose to invoice in euro despite the USD dominance in global trade, though the latter is rarely stated explicitly. Some firms also mitigate exposure by using higher mark-ups or price-adjustment clauses for transactions invoiced in foreign currency.

9 Conclusion

This paper provides a novel firm-level measure of hoarded labor and studies its implications for corporate financial decisions. Specifically, we formalize and find empirical support for a labor-hoarding channel of risk management. The idea is that labor hoarding creates an option-like payoff for the firm: it can be highly profitable in times of high demand, but it also raises the wage bill and thereby reduces cash flows in times of low demand. A risk-averse firm may respond to this increase in cash flow volatility by cutting back risk exposure along other dimensions. We focus on unhedged FX risk, which constitutes a major source of risk for export-oriented German SMEs in our sample.

Using an instrumental-variables approach based on shortage occupations and the occupation-specific importance of vocational training, we find in our baseline specification that a one-standard-deviation increase in hoarded labor is associated with a 0.6-standard-deviation reduction in unhedged

FX risk. The instruments are themselves informative about the drivers of firms' labor hoarding, capturing occupation-specific difficulties in filling positions. Going forward, one may also investigate amplification effects: as certain occupations become more scarce, firms may choose to hoard more labor in these occupations, thereby aggravating the shortage.

Two measurement challenges—measuring hoarded labor and measuring firms' risk-management strategies—have stood in the way so far, and we propose a novel way to address them. Our approach, however, is currently limited to the cross-section of firms, in particular because our measure of hoarded labor is tied to eased-access episodes of STW. An interesting open question is how this window of opportunity for measuring hoarded labor can be used to validate other, more widely available proxies, for example, those based on hiring and exit patterns.

While FX risk is a natural and important risk-adjustment margin for the firms in our context, it is less central, for example, for U.S. SMEs that primarily sell within the U.S. For such firms, other financial risk-reduction margins are likely more relevant. It is interesting to further understand a "pecking order" of financial risk-reduction strategies in response to heightened risk on the labor side across different institutional and product-market environments.

Bibliography

Acabbi, E. M., and A. Alati (2021): "Defusing Leverage: Liquidity Management and Labor Contracts," *Working Paper*.

Adams, P., and A. Verdelhan (2022): "Exchange Rate Risk in Public Firms," *Working Paper*.

Agrawal, A. K., and D. A. Matsa (2013): "Labor Unemployment Risk and Corporate Financing Decisions," *Journal of Financial Economics*, 108(2), 449–470.

Alfaro, L., M. Calani, and L. Varela (2021): "Granular Corporate Hedging under Dominant Currency," *NBER Working Paper No. 28910*.

——— (2024): "Firms, Currency Hedging, and Financial Derivatives," in *Handbook of Financial Integration*, pp. 340–370. Edward Elgar Publishing.

Andrews, I., J. Sock, and L. Sun (2023): "Weak Instruments in IV Regression: Theory and Practice," *Annual Review of Economics*, 11, 727–53.

Antoni, M., K. Koller, M.-C. Laible, and F. Zimmermann (2018): “Orbis-ADIAB: From Record Linkage Key to Research Dataset,” *FDZ-Methodenreport 04/2018*.

Arellano, C., Y. Bai, and P. J. Kehoe (2019): “Financial Frictions and Fluctuations in Volatility,” *Journal of Political Economy*, 127(5), 2049–2103.

Baghai, R. P., R. C. Silva, V. Thell, and V. Vig (2021): “Talent in Distressed Firms: Investigating the Labor Costs of Financial Distress,” *Journal of Finance*, 76(6), 2907–2961.

Bentolila, S., and G. Bertola (1990): “Firing Costs and Labour Demand: How Bad is Eurosclerosis?,” *Review of Economic Studies*, 57(3), 381–402.

Bergeaud, A., C. Malgouyres, C. Mazet-Sonilhac, and S. Signorelli (2025): “Technological Change and Domestic Outsourcing,” *Journal of Labor Economics*, 43(4), 1135–1168.

Biddle, J. E. (2014): “Retrospectives: The Cyclical Behavior of Labor Productivity and the Emergence of the Labor Hoarding Concept,” *Journal of Economic Perspectives*, 28(2), 197–212.

Boehm, C. E., and N. Pandalai-Nayar (2022): “Convex Supply Curves,” *American Economic Review*, 112(12), 3941–3969.

Boz, E., C. Casas, G. Georgiadis, G. Gopinath, H. Le Mezo, A. Mehl, and T. Nguyen (2022): “Patterns of Invoicing Currency in Global Trade: New Evidence,” *Journal of International Economics*, 136, 103604.

Brinkmann, C., S. Jäger, M. Kuhn, F. Saidi, and S. Wolter (2024): “Short-Time Work Extensions,” *NBER Working Paper No. 33112*.

Burnside, C., M. Eichenbaum, and S. Rebelo (1993): “Labor Hoarding and the Business Cycle,” *Journal of Political Economy*, 101(2), 245–273.

Caggese, A., V. Cuñat, and D. Metzger (2019): “Firing the Wrong Workers: Financing Constraints and Labor Misallocation,” *Journal of Financial Economics*, 133(3), 589–607.

Cahuc, P. (2024): “The Micro and Macroeconomics of Short-Time Work,” *Handbook of Labor Economics (forthcoming)*.

Campello, M., J. Gao, J. Qiu, and Y. Zhang (2018): "Bankruptcy and the Cost of Organized Labor: Evidence from Union Elections," *Review of Financial Studies*, 31(3), 980–1013.

Cestone, G., C. Fumagalli, F. Kramarz, and G. Pica (2024): "Exploiting Growth Opportunities: The Role of Internal Labour Markets," *Review of Economic Studies*, 91(5), 2676–2716.

Clark, C. S. (1973): "Labor Hoarding in Durable Goods Industries," *American Economic Review*, 63(5), 811–824.

Crouzet, N., Z. He, V. Lyonnet, and Y. Ma (2025): "Why don't Old Firms Do New Things?," *Working Paper*.

Dauth, W., and J. Eppelsheimer (2020): "Preparing the Sample of Integrated Labour Market Biographies (SIAB) for Scientific Analysis: A Guide," *Journal for Labour Market Research*, 54(1), 10.

Dhyne, E., A. K. Kikkawa, T. Komatsu, M. Mogstad, and F. Tintelnot (2025): "Firm Responses and Wage Effects of Foreign Demand Shocks with Fixed Labor Costs and Monopsony," *American Economic Review*, 115(12), 4328–4368.

Donangelo, A., F. Gourio, M. Kehrig, and M. Palacios (2019): "The Cross-Section of Labor Leverage and Equity Returns," *Journal of Financial Economics*, 132(2), 497–518.

Dustmann, C., and U. Schönberg (2012): "What Makes Firm-Based Vocational Training Schemes Successful? The Role of Commitment," *American Economic Journal: Applied Economics*, 4(2), 36–61.

Favilukis, J., X. Lin, and X. Zhao (2020): "The Elephant in the Room: The Impact of Labor Obligations on Credit Markets," *American Economic Review*, 110(6), 1673–1712.

Fay, J. A., and J. L. Medoff (1985): "Labor and Output Over the Business Cycle: Some Direct Evidence," *American Economic Review*, 75(4), 638–655.

Froot, K. A., D. S. Scharfstein, and J. C. Stein (1993): "Risk Management: Coordinating Corporate Investment and Financing Policies," *Journal of Finance*, 48(5), 1629–1658.

Ganzer, A., A. Schmucker, J. Stegmaier, and S. Wolter (2023): "Establishment History Panel 1975-2022," *FDZ-Datenreport 15/2023*.

Ghaly, M., V. Anh Dang, and K. Stathopoulos (2017): "Cash Holdings and Labor Heterogeneity: the Role of Skilled Labor," *Review of Financial Studies*, 30(10), 3636–3668.

Giroud, X., and H. M. Mueller (2017): "Firm Leverage, Consumer Demand, and Employment Losses during the Great Recession," *Quarterly Journal of Economics*, 132(1), 271–316.

Giupponi, G., and C. Landais (2023): "Subsidizing Labour Hoarding in Recessions: The Employment and Welfare Effects of Short-time Work," *Review of Economic Studies*, 90(4), 1963–2005.

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift (2020): "Bartik Instruments: What, When, Why, and How," *American Economic Review*, 110(8), 2586–2624.

Gopinath, G., and O. Itskhoki (2022): "Dominant Currency Paradigm: A Review," *Handbook of International Economics*, 6, 45–90.

Grienberger, K., M. Janser, and F. Lehmer (2023): "The Occupational Panel for Germany," *Journal of Economics and Statistics*, 243(6), 711–724.

Hackbarth, D., and T. Johnson (2015): "Real Options and Risk Dynamics," *The Review of Economic Studies*, 82(4), 1449–1482.

Huang, P., H.-Y. Huang, and Y. Zhang (2019): "Do Firms Hedge with Foreign Currency Derivatives for Employees?," *Journal of Financial Economics*, 133(2), 418–440.

Jäger, S., J. Heining, and N. Lazarus (2024): "How Substitutable are Workers? Evidence from Worker Deaths," *NBER Working Paper No. 30629*.

Jäger, S., B. Schoefer, and J. Heining (2021): "Labor in the Boardroom," *Quarterly Journal of Economics*, 136(2), 669–725.

Jiang, W. (2017): "Have Instrumental Variables Brought Us Closer to the Truth," *Review of Corporate Finance Studies*, 6(2), 127–140.

Kagerl, C. (2024): "The Employment and Windfall Effects of Short-Time Work: Evidence from Germany," *mimeo*.

Kalemli-Ozcan, S., B. Sorensen, C. Villegas-Sanchez, V. Volosovych, and S. Yesiltas (2015): "How to Construct Nationally Representative Firm Level Data from the Orbis Global Database," *NBER Working Paper No. 21558*.

Kim, H. (2020): "How does labor market size affect firm capital structure? Evidence from large plant openings," *Journal of Financial Economics*, 138(1), 277–294.

Kuhn, M., J. Luo, I. Manovskii, and X. Qiu (2023): "Coordinated Firm-Level Work Processes and Macroeconomic Resilience," *Journal of Monetary Economics*, 137, 107–127.

Kuo, C.-W. (2024): "Short-Time Work, Labor Hoarding, and Curtailed Hiring: Establishment-Level Evidence from Japan," *Journal for Labour Market Research*, 58(1), 7.

Kuzmina, O. (2023): "Employment Flexibility and Capital Structure: Evidence from a Natural Experiment," *Management Science*, 69(9), 4992–5017.

Levin-Konigsberg, G., H. Stein, V. G. Averell, and C. L. Castañon (2023): "Risk Management and Derivatives Losses," *FRB of Boston Working Paper No. 23-8*.

Lyonnet, V., J. Martin, and I. Mejean (2022): "Invoicing Currency and Financial Hedging," *Journal of Money, Credit and Banking*, 54(8), 2411–2444.

Mohr, S. (2015): "Übernahme nach der Ausbildung in Ost-und Westdeutschen Betrieben," *Berufsbildung in Wissenschaft und Praxis*, 5, 4–5.

Moser, C., F. Saidi, B. Wirth, and S. Wolter (2021): "Credit Supply, Firms, and Earnings Inequality," *CEPR Discussion Paper No. DP16123*.

Oi, W. Y. (1962): "Labor as a Quasi-Fixed Factor," *Journal of Political Economy*, 70(6), 538–555.

Okun, A. M. (1963): *Potential GNP: Its Measurement and Significance*. Cowles Foundation for Research in Economics at Yale University (Reprinted from the 1962 Proceedings of the Business and Economic Statistics Section of the American Statistical Association), Available at https://cowles.yale.edu/node/142137.

Rotemberg, J. J., and L. H. Summers (1990): "Inflexible Prices and Procyclical Productivity," *Quarterly Journal of Economics*, 105(4), 851–874.

Sauer, S., M. Schasching, and K. Wohlrabe (2023): *Handbook of ifo Surveys*, no. 100. ifo Beiträge zur Wirtschaftsforschung.

Schmalz, M. C. (2018): "Unionization, Cash, and Leverage," *CEPR Discussion Paper No. 12595.*

Serfling, M. (2016): "Firing Costs and Capital Structure Decisions," *Journal of Finance*, 71(5), 2239–2286.

Simintzi, E., V. Vig, and P. Volpin (2015): "Labor Protection and Leverage," *Review of Financial Studies*, 28(2), 561–591.

Simon, H. (1996): "Hidden Champions: Lessons from 500 of the World's Best Unknown Companies," *Harvard Business School Press.*

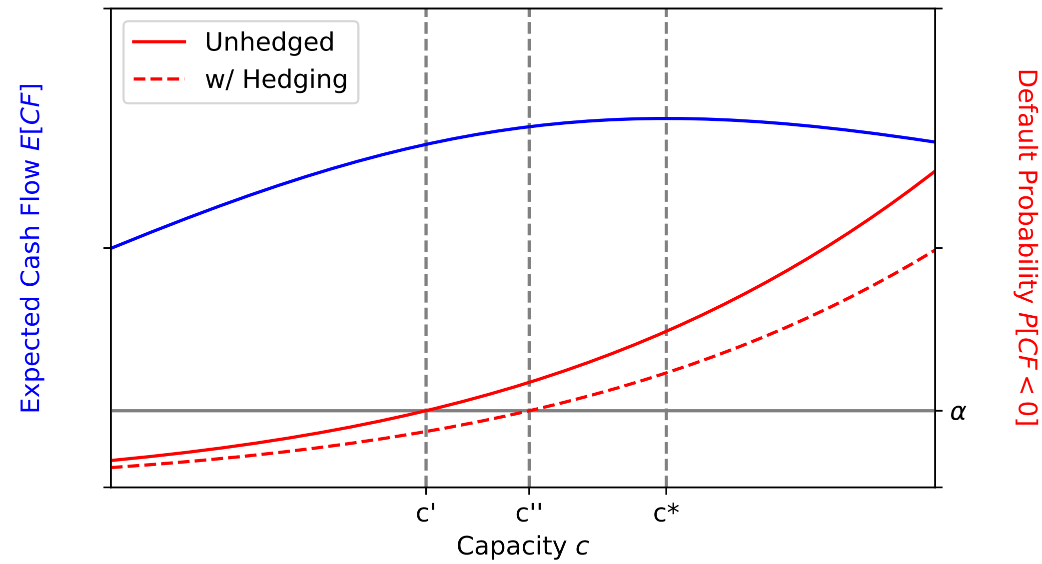
Stock, J., and M. Yogo (2005): "Testing for Weak Instruments in Linear IV Regression," *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, pp. 80–108.

Stulz, R. M. (2024): "Risk, the Limits of Financial Risk Management, and Corporate Resilience," *NBER Working Paper No. 32882.*

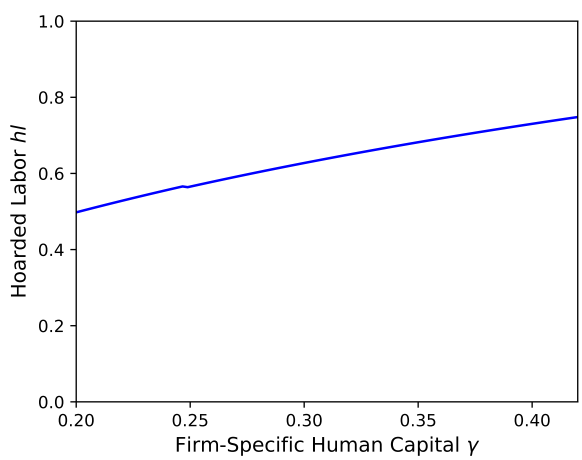
Figures

Figure 1: Model

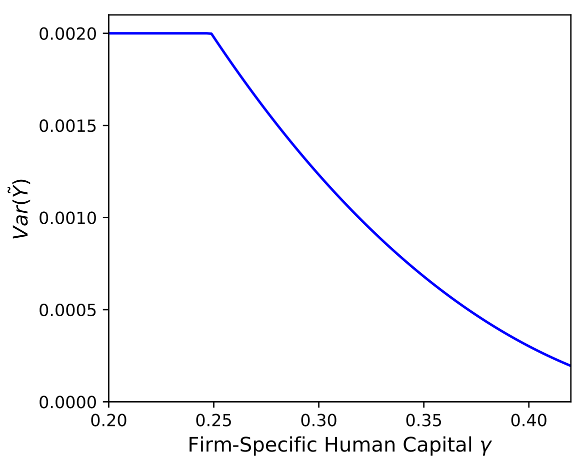
(a) Core Trade-Off between Capacity and Default Risk



(b) Hoarded Labor hl

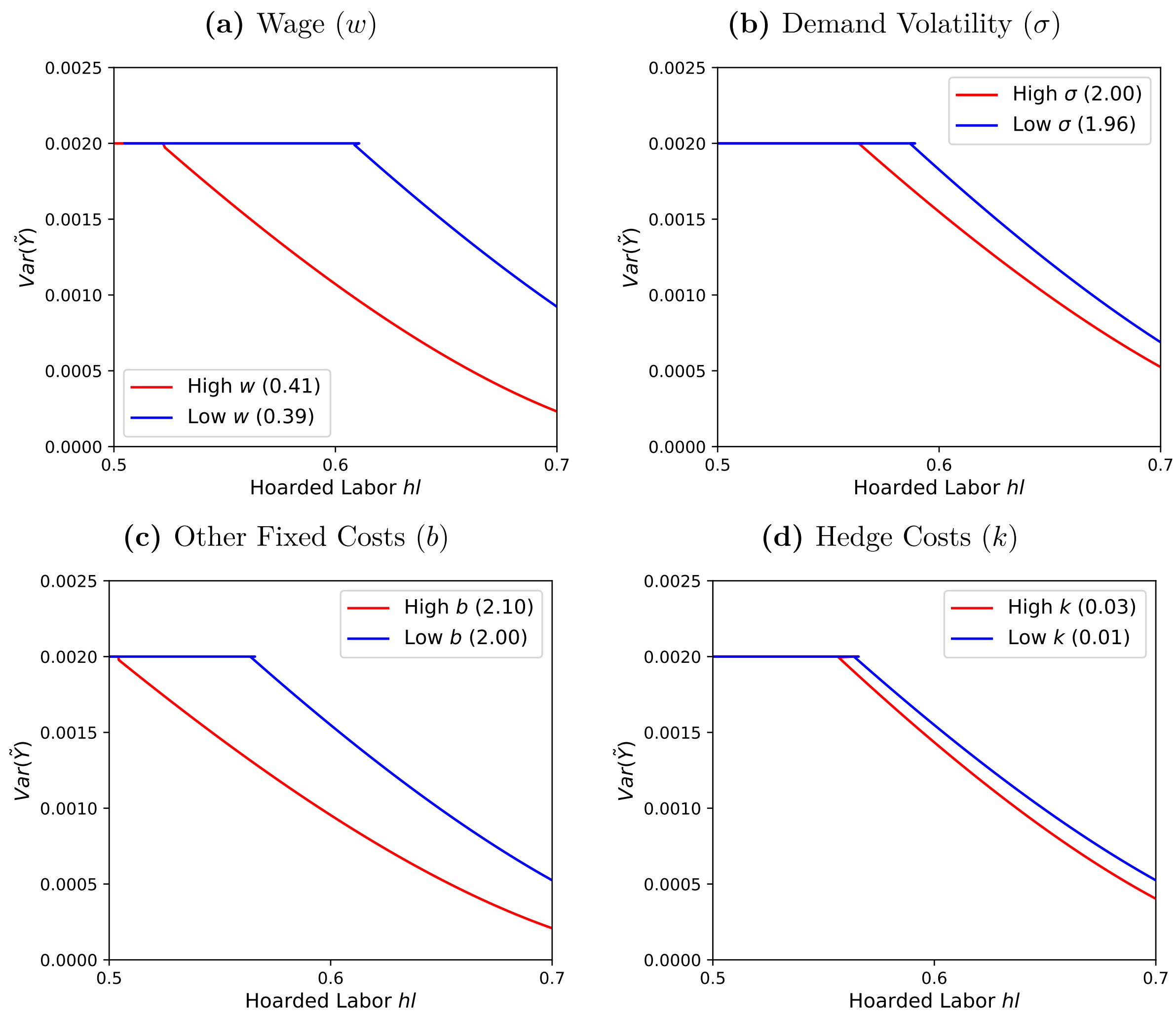


(c) Var of Hedged Exchange Rate $Var(\tilde{Y})$



Notes: Panel (a) illustrates, for a fixed level of firm-specific human capital γ, the core trade-off around the choice of fixed labor (γc) between expected cash flow (blue, LHS scale) and default probability (red, RHS scale). c^* denotes the optimal capacity choice in the absence a cap on the default probability. This capacity choice is infeasible for a firm operating under an upper bound α for its default probability, as indicated by the black horizontal line drawn at level α. c' denotes the optimal capacity under the constraint without hedging. Hedging relaxes the constraint as illustrated by the downward shift of the dashed red line (*w/ Hedging*) compared to the solid red line (*Unhedged*), making the larger capacity c'' feasible. Panel (b) and (c) shows how optimal *hoarded labor*, $hl = \gamma(c - E[\min(X, c)])$, and the *variance of the hedged exchange rate*, $Var(\tilde{Y}) = 2p(a - h)^2$, change as a function of firm-specific human capital γ. The constraint considered is $P[CF < 0|Y = (1 - a)] < \alpha$. The model is numerically solved for the following set of parameters: $\mu = 10, \sigma = 2, b = 2, a = 0.1, p = 0.1, w = 0.4, \alpha = 0.01, k = 0.01, q_{min} = 0.02$.

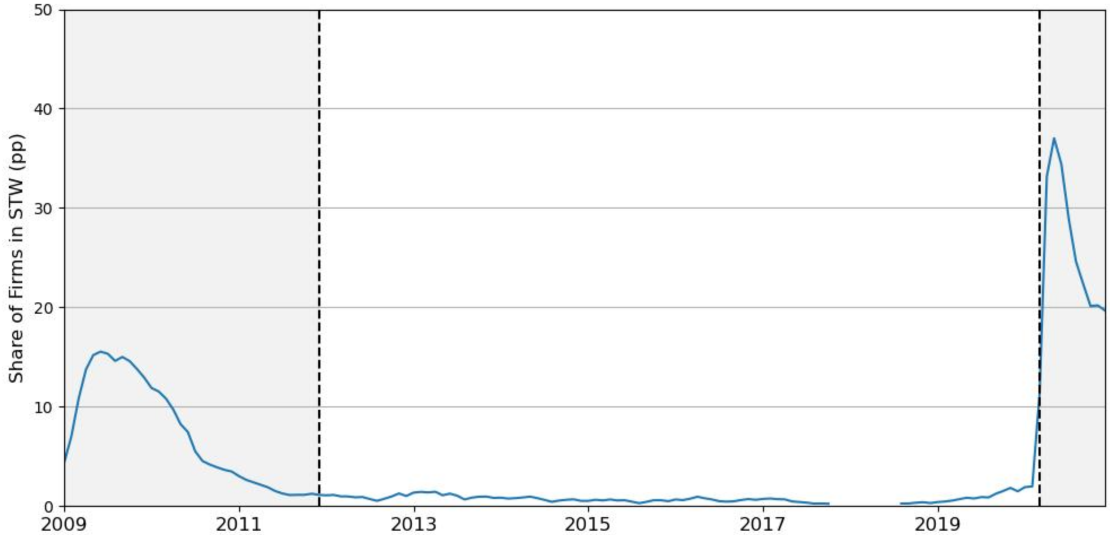
Figure 2: Model: Comparative Statics



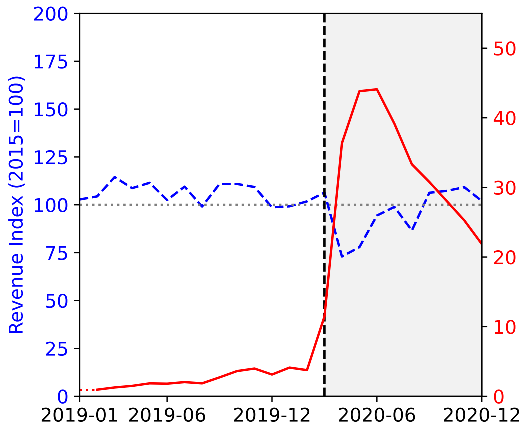
Notes: The figure shows comparative statics in w (Panel (a)), σ (Panel (b)), b (Panel (c)), and k (Panel (d)) of the optimal choice of hoarded labor (hl, x-axis) and the variance of the hedged exchange rate ($\tilde{Y}$, y-axis). The baseline parameter specification is as before: $\mu = 10, \sigma = 2, b = 2, a = 0.1, p = 0.1, w = 0.4, \alpha = 0.01, k = 0.01, q_{min} = 0.02$.

Figure 3: STW Usage, Total and by Industry (Eased-Access Episodes in gray)

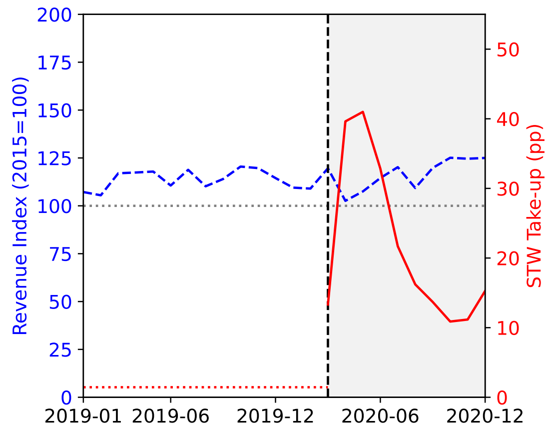
(a) STW Usage Over Time



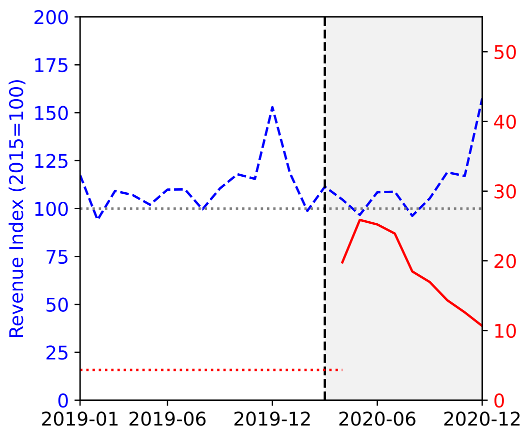
(b) Manufacturing



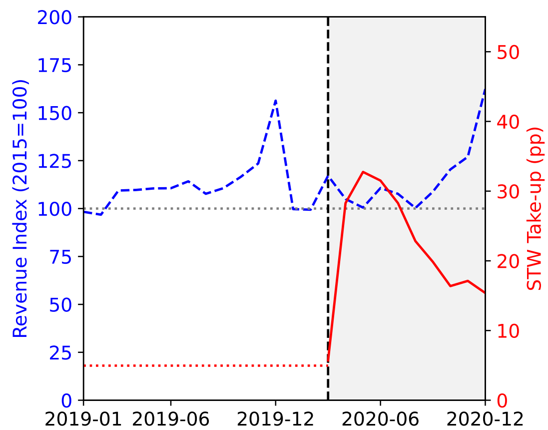
(c) Wholesale and Retail Trade



(d) Information and Communication

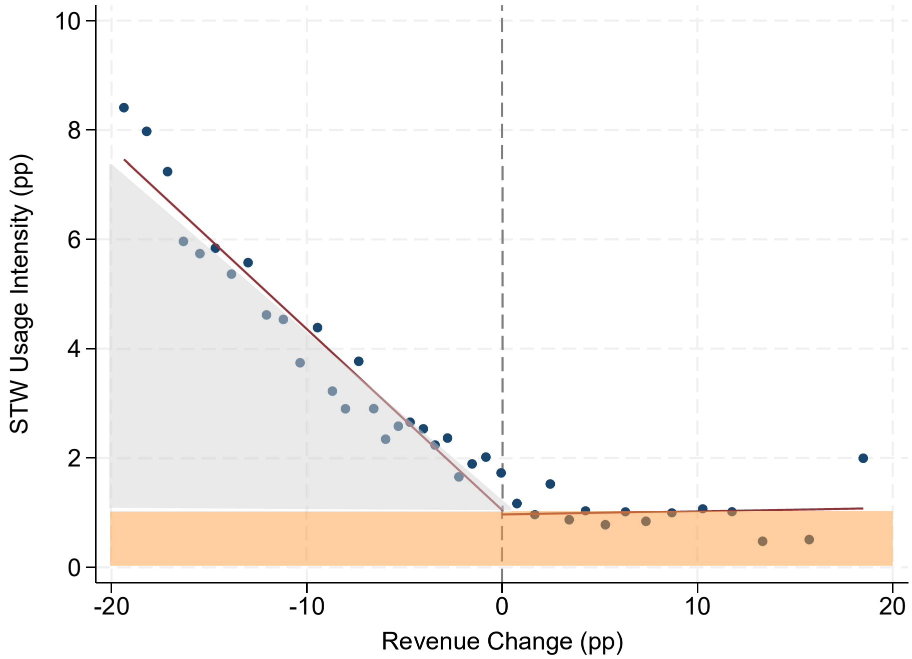


(e) Prof., Scientific, Technical Activities



Notes: Panel (a) shows the monthly share of firms in STW from 2009 until 2020. The shaded areas indicate episodes of eased access to STW (2009-2011, since March 2020). Panels (b)-(d) plots monthly industry-wide revenue (blue, LHS scale) against the share of firms in STW per industry (red, RHS scale) for the four largest industries. Revenue is a value index, normalized to 100 in 2015 (raw series), from the Federal Statistical Office(tables 42152-0001, 45212-0005 and 47414-0005). Gaps in the data come from data protection (fewer than 20 firms, line below which no data is available shown in dotted red). The sample in Panel (a) consists of all firms with available revenue information in 2019 and 2020 that can be matched to the administrative employment data (9,145 in 2020), and further restricted to those with y-o-y revenue changes in [−20%.20%] in Panels (b)-(d) (see section 4 for details).

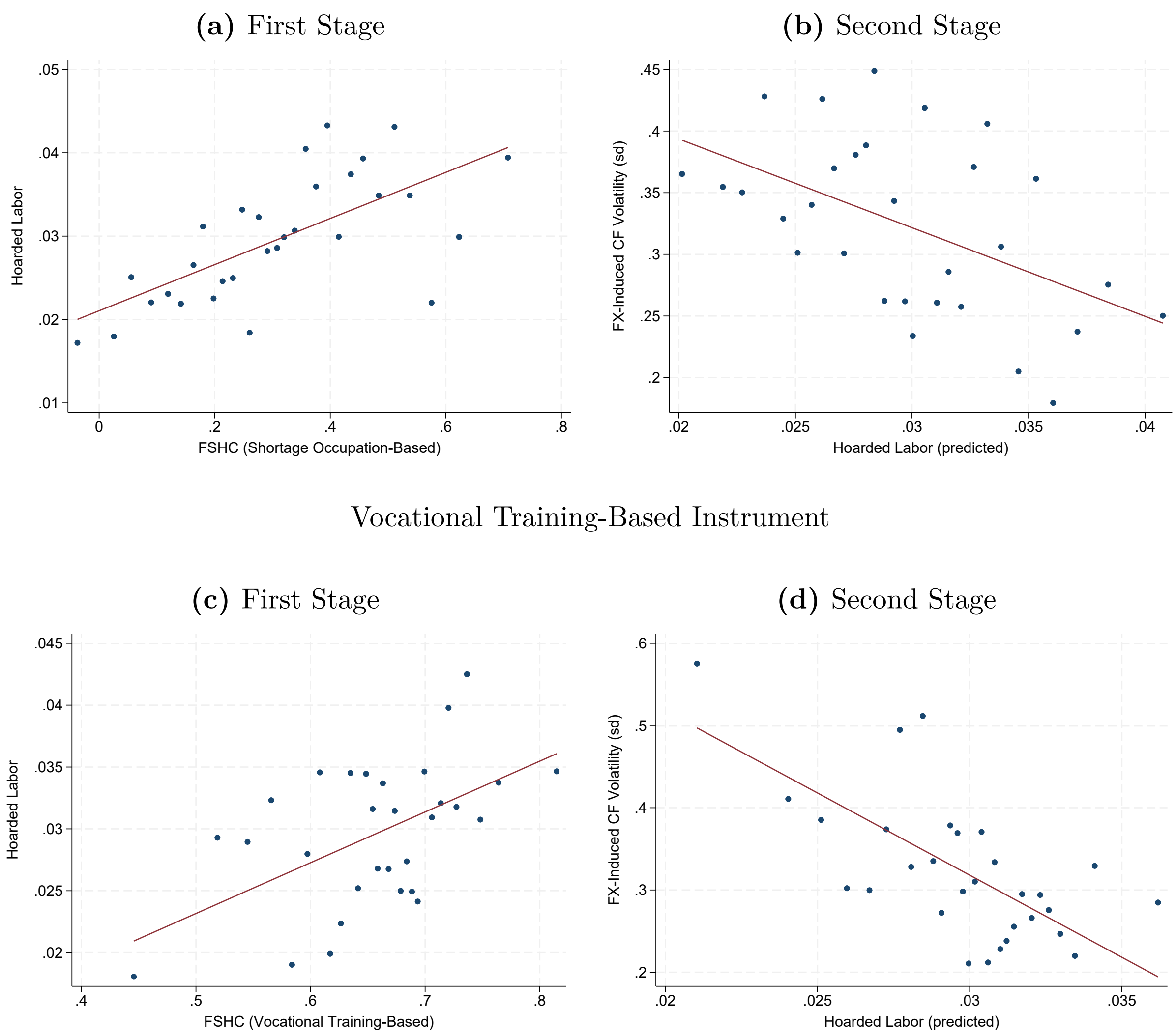
Figure 4: Measuring Hoarded Labor



Notes: The figure shows a binned scatterplots of average STW usage intensity between June and December 2020 against the year-on-year revenue change 2020 (in pp). STW usage intensity is defined as the average monthly worker-equivalent of the reduction in work relative to employment (for details see section 3.3). We define *Hoarded Labor* as residual STW Usage Intensity after controlling for the change in revenue (indicated by the orange shaded area). The results are based on firms with FX data (see panel (b) of Table 1).

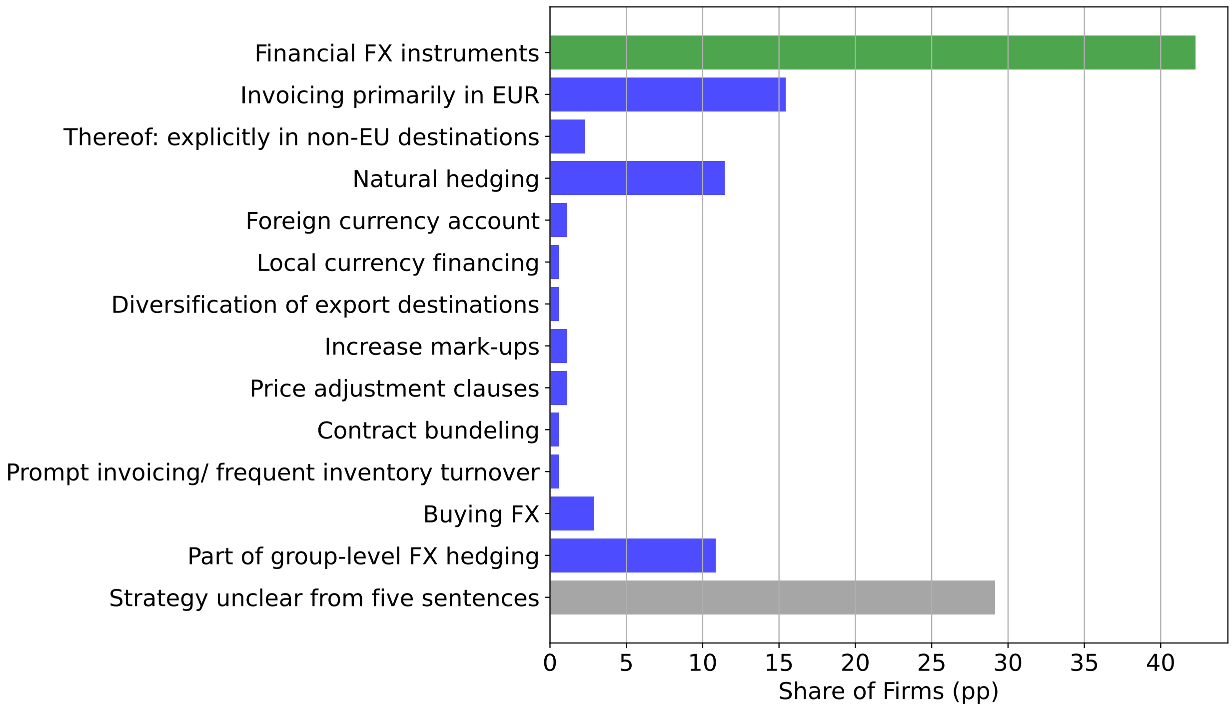
Figure 5: Effect of Hoarded Labor on FX-Induced CF Volatility

Shortage Occupation-Based Instrument



Notes: The figure shows binned scatterplots using the shortage occupation-based instrument (vocational share-based instrument) of the first stage in Panel (a) (Panel (c)) and second stage in Panel (b) (Panel (d)) of the design (R3). The same set of controls are inluded as in the baseline specification (columns 1 and 2 of Panels (a) and (b) of Table 5). For details on the construction of the measures *FX-induced CF Volatility* and *Hoarded Labor* see sections 6.2 and 3.3.

Figure 6: FX-Hedging Strategies



Notes: The figure shows a manual classification of the five most relevant sentences in firms' annual reports (2019) upon which the AI-classification is based. The sample consists of firms with (AI-classified) active FX management among 500 randomly selected firms of out of 4,613 classified in total (see Appendix B5 for details).

Tables

Table 1: Summary Statistics

(a) Full Sample

	Mean	SD	p5	p50	p95	N Firms
Core Financial Information (2019)						
Assets (mil EUR)	160.393	2435.800	2.049	31.206	362.253	6913
Revenue (mil EUR)	139.312	1180.835	3.717	45.918	360.113	6913
Employees	351.919	1535.582	22.000	165.000	1123.000	6913
Leverage (pp)	59.091	40.897	15.196	58.348	98.241	6913
Cash/Assets (pp)	12.124	16.090	0.011	5.568	47.013	6913
ROA (pp)	6.474	15.908	-10.470	4.330	28.100	6913
Value Added per Employee (mil EUR)	0.129	0.866	0.036	0.081	0.307	5104
Firm-Level Employment Characteristics (2019)						
Avrg Age (years)	43.201	4.002	36.406	43.309	49.571	6913
Avrg Wage (EUR, daily, FT)	117.721	34.203	63.431	115.821	177.833	6913
Avrg Tenure (years)	9.692	4.083	3.718	9.320	16.896	6913
Shares by Education: Low Education Level	0.088	0.068	0.000	0.075	0.214	6913
Shares by Education: Vocational Training	0.652	0.192	0.233	0.701	0.885	6913
Shares by Education: Degree from University/FH	0.234	0.202	0.026	0.172	0.686	6913
Labor Hoarding Measures						
Labor Hoarding (binary)	0.338	0.473	0.000	0.000	1.000	6913
Hoarded Labor (based on 2020)	0.019	0.044	0.000	0.000	0.108	6913

(b) Firms with FX Data

	Mean	SD	p5	p50	p95	N Firms
Core Financial Information (2019)						
Assets (mil EUR)	305.753	4118.036	9.136	46.007	505.907	2352
Revenue (mil EUR)	236.749	1823.663	15.344	72.968	647.062	2352
Employees	450.734	2510.383	34.000	221.000	1182.000	2352
Leverage (pp)	59.271	31.562	16.001	58.843	97.774	2352
Cash/Assets (pp)	9.532	13.017	0.004	4.097	37.905	2352
ROA (pp)	7.447	13.685	-10.770	6.135	28.750	2352
Value Added per Employee (mil EUR)	0.168	1.499	0.045	0.092	0.275	1661
Firm-Level Employment Characteristics (2019)						
Avrg Age (years)	42.825	3.507	36.678	43.058	48.375	2352
Avrg Wage (EUR, daily, FT)	132.820	29.749	84.744	131.630	182.532	2352
Avrg Tenure (years)	10.513	4.233	4.211	10.143	18.050	2352
Shares by Education: Low Education Level	0.086	0.062	0.000	0.075	0.202	2352
Shares by Education: Vocational Training	0.626	0.188	0.208	0.682	0.843	2352
Shares by Education: Degree from University/FH	0.267	0.203	0.053	0.194	0.714	2352
Labor Hoarding Measures						
Labor Hoarding (binary)	0.477	0.500	0.000	0.000	1.000	2352
Hoarded Labor (based on 2020)	0.030	0.053	0.000	0.000	0.136	2352
Hoarded Labor (based on 2009)	0.027	0.211	0.000	0.000	0.120	2276
Information on Exports and FX-Volatility						
Export Share	0.441	0.275	0.020	0.450	0.900	2352
sd net gains	0.323	0.615	0.002	0.117	1.309	2352
max net loss	0.496	1.026	0.000	0.138	2.165	2352
1(Exports to Outside Europe)	0.822	0.383	0.000	1.000	1.000	1192
1(Financial Hedging 2019)	0.265	0.441	0.000	0.000	1.000	2352
1(Active FX Management (w/ AI) 2019)	0.422	0.494	0.000	0.000	1.000	2348
Number of Banks	2.619	1.380	1.000	2.000	5.000	2224

Notes: The table reports firm-level summary statistics for the full sample in Panel (a) and for the subsample of firms with FX data in Panel (b). For details on the labor-hoarding measures see section 3.3, details on *FX-Induced CF Volatility* see section 6.1 and details on *Financial Hedging* and *Active FX Management w/ AI* see Appendices B4 and B5.

Table 2: Comovement of Changes in Profitability with Industry-Wide Upturns and Downturns by Labor Hoarding

	Dep. Variable:					
	ROA (Δ yoy)			CF (Δ yoy)		
	(1)	(2)	(3)	(4)	(5)	(6)
Labor Hoarding	-0.080			-0.097***		
	(0.04)			(0.02)		
Labor Hoarding × Δ Industry-Level Demand	0.461	0.759**	0.664**	0.501***	0.486**	0.483**
	(0.37)	(0.26)	(0.18)	(0.10)	(0.12)	(0.13)
Year x Industry FEs	Yes	Yes	No	Yes	Yes	No
Year x Industry x Region FEs	No	No	Yes	No	No	Yes
Firm FEs	No	Yes	Yes	No	Yes	Yes
N Firms	4804	4804	4804	4799	4799	4799
R^2	0.002	0.135	0.151	0.002	0.142	0.155
Adj. R^2	0.001	0.010	0.010	0.001	0.017	0.015
N Observations	38,477	38,339	38,250	38,428	38,291	38,204

Notes: The table reports the results of the specification (R1) in a firm-year panel from 2010-2020. The results are based on the full sample of firms (see panel (a) of Table 1). *Labor Hoarding* is a binary firm-level variable that takes the value of 1 if the firm uses STW in the eased-access episode in 2020 (June-December), for details see section 3.3. Δ *Industry-Level Demand* is the year-on-year change in the ifo Business Climate index (6m-ahead expectations, provided by the ifo Institut) per sector as of March each year. Robust standard errors, clustered at the industry level, are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Total vs. FX-Induced CF Volatility

	Dep. Variable: Cash Flow Volatility (sd) Total					FX-Induced	
	(1)	(2)	(3)	(4)	(5)	sd	max
Labor Hoarding	0.083						
	(0.34)						
Hoarded Labor		4.048	3.322	1.778	-0.668	-0.450**	-0.764**
		(3.21)	(3.03)	(3.20)	(3.43)	(0.20)	(0.37)
Log Assets	0.922***	0.929***	0.846***	0.872***	0.877***	0.065***	0.099***
	(0.15)	(0.15)	(0.19)	(0.15)	(0.32)	(0.02)	(0.02)
Revenue Change 19-20	-2.213	-1.729	-2.807	-1.698	0.923	-0.039	-0.037
	(1.75)	(1.76)	(2.09)	(1.76)	(1.99)	(0.16)	(0.26)
Value Added per Employee			1.510***				
			(0.24)				
ROA (pp)				-0.065***			
				(0.02)			
Export Share					2.172**	0.456***	0.692***
					(0.91)	(0.06)	(0.10)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.099	0.099	0.140	0.106	0.135	0.112	0.092
Adj. R^2	0.071	0.071	0.107	0.079	0.106	0.082	0.061
N Firms	6,463	6,463	4,847	6,463	2,319	2,319	2,319

Notes: The table reports estimated OLS coefficients from specification (R2). Columns 1-5 use total CF volatility on the LHS, while column 6 and 7 use FX-Induced CF Volatility on the LHS. Two versions of the variable *FX-Induced CF Volatility* are considered: standard deviation of net FX gains to revenue (*sd*) and maximum of net FX losses to revenue (*max*) (see section 6.2 for details). Column 1 uses a binary variable that takes the value of 1 if a firm uses STW during the eased-access episode of 2020 (*Labor Hoarding*) while all other columns consider the measure *Hoarded Labor*.

Table 4: Summary Statistics of 10 Largest Occupations

	2019				2018				Voc Share	Short
Occupations in	Mean	p50	p90	N	Mean	p50	p90	N		
Machine-building and -operating, Specialist	9.95	6.03	24.57	1597	10.14	6.06	25.11	1576	87.26	1
Business organisation and strategy, Specialist	7.07	4.36	15.62	1978	7.18	4.37	15.49	1949	71.30	0
Chemistry, Specialist	10.55	2.80	36.29	559	10.55	2.93	35.90	555	84.87	0
Warehousing and logistics, in postal and other delivery services, and in cargo handling, Unskilled or semi-skilled	6.45	2.99	17.49	1493	6.67	3.12	18.01	1488	64.63	1
Metalworking, Specialist	7.52	3.16	21.93	815	7.80	3.37	22.73	800	89.43	1
Office clerks and secretaries, Specialist	4.45	2.13	10.19	1925	4.63	2.22	10.39	1926	76.47	0
Energy technologies (technical), Specialist	2.87	1.63	6.11	1122	2.91	1.69	6.37	1107	90.08	0
Production planning and scheduling (technical), Complex specialist	3.08	2.33	6.39	1641	3.11	2.33	6.54	1624	69.40	0
Purchasing and sales, Complex specialist	4.62	2.51	10.67	1850	4.67	2.57	10.53	1832	67.05	0
Warehousing and logistics, in postal and other delivery services, and in cargo handling, Specialist	4.22	2.46	9.09	1642	4.29	2.44	8.84	1634	79.11	0

Notes: The table shows summary statistics of the firm-level shares of the 10 largest occupations in the sample (as of 2019). All numbers are in percent. The last two columns show occupation-level information on the aggregare share with vocational training or whether it is a shortage occupation. The results are based on firms with FX data (see panel (b) of Table 1).

Table 5: Impact of Hoarded Labor on FX-Induced CF Volatility Using FSHC as Instrument

(a) Shortage Occupation-Based

	Dep. Variable: FX-Induced CF Volatility					
	OLS		2SLS		Reduced Form	
	sd	max	sd	max	sd	max
Hoarded Labor	-0.450**	-0.764**	-7.192***	-13.069***		
	(0.203)	(0.371)	(2.654)	(4.750)		
Log Assets	0.065***	0.099***	0.030	0.036	0.067***	0.102***
	(0.016)	(0.021)	(0.020)	(0.033)	(0.016)	(0.020)
Export Share	0.457***	0.692***	0.512***	0.793***	0.455***	0.690***
	(0.059)	(0.098)	(0.067)	(0.113)	(0.058)	(0.097)
Revenue Change 19-20	-0.039	-0.037	-1.308**	-2.353**	0.016	0.053
	(0.158)	(0.258)	(0.536)	(0.940)	(0.147)	(0.235)
FSHC (Shortage Occupation-Based)					-0.199***	-0.362***
					(0.062)	(0.111)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Instrument 1st Stage			.028	.028		
Partial R Squared 1st Stage			.009	.009		
Kleibergen-Paap F-statistic			23.036	23.036		
N Firms	2,319	2,319	2,319	2,319	2,319	2,319

(b) Vocational Training-Based

	Dep. Variable: FX-Induced CF Volatility					
	OLS		2SLS		Reduced Form	
	sd	max	sd	max	sd	max
Hoarded Labor	-0.450**	-0.764**	-19.978***	-32.704***		
	(0.203)	(0.371)	(7.686)	(12.453)		
Log Assets	0.065***	0.099***	-0.035	-0.064	0.065***	0.099***
	(0.016)	(0.021)	(0.046)	(0.072)	(0.016)	(0.020)
Export Share	0.457***	0.692***	0.617***	0.954***	0.430***	0.648***
	(0.059)	(0.098)	(0.118)	(0.195)	(0.057)	(0.095)
Revenue Change 19-20	-0.039	-0.037	-3.714**	-6.049**	-0.015	0.006
	(0.158)	(0.258)	(1.462)	(2.379)	(0.143)	(0.232)
FSHC (Vocational Training-Based)					-0.820***	-1.342***
					(0.215)	(0.339)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Instrument 1st Stage			.041	.041		
Partial R Squared 1st Stage			.003	.003		
Kleibergen-Paap F-statistic			11.065	11.065		
N Firms	2,319	2,319	2,319	2,319	2,319	2,319

Notes: The table reports the estimated coefficients from specification (R3) instrumenting *Hoarded Labor* with the shortage occupation-based instrument (Panel (a)) and with the vocational training-based instrument (Panel (b)). In each panel, the first two columns show the OLS, the following two columns the 2SLS and the final two columns the reduced form estimates. Two versions of the variable *FX-Induced CF Volatility* are considered: standard deviation of net FX gains to revenue (*sd*) and maximum of net FX losses to revenue (*max*) (see section 6.2 for details). For details on the construction of *Hoarded Labor* see section 3.3. Control variables are as of 2019 (or available information in Dafne as of May 2022 for *Export Share*). Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Heterogeneity by Hedging Strategy

	Dep. Variable: FX-Induced CF Volatility					
	2SLS					
Heterogeneity Dimension:	High Cash Holdings		FX Derivatives		Active FX Management	
	sd	max	sd	max	sd	max
Hoarded Labor	-7.337**	-13.522***	-4.233*	-11.279**	-5.261**	-10.685**
	(2.856)	(5.037)	(2.458)	(4.666)	(2.502)	(4.426)
Heterogeneity Dimension × Hoarded Labor	0.555	1.528	-9.462*	-5.695	-7.350*	-8.933
	(3.427)	(6.092)	(5.606)	(8.251)	(4.261)	(7.260)
Heterogeneity Dimension	-0.007	-0.055	0.411**	0.324	0.317**	0.433*
	(0.108)	(0.187)	(0.186)	(0.266)	(0.138)	(0.232)
Log Assets	0.031	0.036	0.019	0.023	0.025	0.028
	(0.020)	(0.034)	(0.022)	(0.035)	(0.022)	(0.035)
Export Share	0.510***	0.793***	0.444***	0.738***	0.459***	0.713***
	(0.068)	(0.114)	(0.072)	(0.116)	(0.070)	(0.115)
Revenue Change 19-20	-1.299**	-2.340**	-1.173**	-2.288**	-1.474**	-2.558**
	(0.539)	(0.952)	(0.521)	(0.920)	(0.612)	(1.045)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
F main effect	11.272	11.272	11.884	11.884	11.489	11.489
F interaction	5.228	5.228	4.774	4.774	8.799	8.799
N Firms	2,319	2,319	2,319	2,319	2,316	2,316

Notes: This table reports 2SLS estimates from a specification analogous to (R3) allowing for heterogeneity of the effect depending on whether the firm has above-median cash holdings (first two columns), uses FX derivatives (next two columns) or actively manages FX risk (final two columns). For details on the construction of the measures for FX derivatives usage or active FX management, see Appendices B4 and B5. Two versions of the variable *FX-Induced CF Volatility* are considered: standard deviation of net FX gains to revenue (*sd*) and maximum of net FX losses to revenue (*max*) (see section 6.2 for details). For details on the construction of *Hoarded Labor* see section 3.3. Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix:

Do Firms Hedge Human Capital?

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A Appendix: Model Proofs

A1 Proof of Lemma 1

We consider the amplitude of the partially hedged exchange rate $q := a - h$, instead of h.

For the density $f(\cdot)$ of a normal distribution with mean μ and variance σ^2 the following property holds:

$$f'(x) = -\frac{(x-\mu)}{\sigma^2} f(x). \tag{A2}$$

Hence,

$$\begin{aligned} E[\min(X,c)] &= \int_{-\infty}^{c} x f(x) dx + \int_{c}^{\infty} c f(x) dx && \text{(A3)} \\ &= -\sigma^2 \int_{-\infty}^{c} -\frac{(x-\mu)}{\sigma^2} f(x) dx + \mu \int_{-\infty}^{c} f(x) dx + \int_{c}^{\infty} c f(x) dx && \text{(A4)} \\ &= -\sigma^2 f(c) + \mu F(c) + c(1 - F(c)), && \text{(A5)} \end{aligned}$$

and

$$\begin{aligned} \partial_c E[\min(X,c)] &= -\sigma^2 f'(c) + (\mu - c) f(c) + (1 - F(c)) && \text{(A6)} \\ &= (1 - F(c)). && \text{(A7)} \end{aligned}$$

With E short-hand for the expected cashflow,

$$E := E[CF_\gamma(c,q)] = E[\min(X,c)]\,[1 - k(a-q) - (1-\gamma)w] - (\gamma wc + b), \tag{A8}$$

it follows that

$$\begin{aligned} \partial_c E &= [1 - k(a-q) - (1-\gamma)w]\,(1 - F(c)) - \gamma w && \text{(A9)} \\ \partial_c^2 E &= -\,[1 - k(a-q) - (1-\gamma)w]\, f(c) \qquad < 0. && \text{(A10)} \end{aligned}$$

For a fixed q, from (A10) and $\lim_{c\to\infty} \partial_c E < 0$, $\partial_c E = 0$ is a necessary and sufficient condition for a unique local maximum, which is also a global one here. Since the optimal solution c^* is larger 0 (otherwise the setup is not interesting), from (A10) we also know that $\partial_c E > 0$ for $c < c^*$. Since $\partial_q E = kE[\min(X,c)] > 0$, the firm chooses the highest possible q.

$\square$

A2 Proof of Proposition 1

We consider the amplitude of the partially hedged exchange rate $q := a - h$, instead of h.

Step 1: Preliminary properties.
For ease of notation we define the following objects and show some preliminary properties first. Denote by $i \in \{o, m, u\}$ the good, neutral and bad realization of the exchange rate. Then the fixed costs, β_2, and marginal return in the different states read

$$\beta_2 := \gamma wc + b \tag{A11}$$

$$\beta_{1i} := \begin{cases} (1+q) - k(a-q) - (1-\gamma)w & \text{for } i = o, Y = (1+a) \\ 1 - k(a-q) - (1-\gamma)w & \text{for } i = m, Y = 1 \\ (1-q) - k(a-q) - (1-\gamma)w & \text{for } i = u, Y = (1-a) \end{cases} \tag{A12}$$

Further, for $i \in \{o, m, u\}$

$$\lambda_i := \frac{\beta_2}{\beta_{1i}}. \tag{A13}$$

Then the derivatives of E read

$$\partial_c E = \beta_{1m}(1 - F(c)) - \gamma w \tag{A14}$$
$$\partial_q E = kE[\min(X, c)] \qquad > 0 \tag{A15}$$
$$\partial_c^2 E = -\beta_{1m} f(c) \qquad < 0 \tag{A16}$$
$$\partial_c \partial_q E = k(1 - F(c)) \qquad > 0 \tag{A17}$$
$$\partial_q^2 E = 0. \tag{A18}$$

Note that

$$P[\min(X, c) < \Omega] = \begin{cases} F[\Omega] & \text{for } \Omega < c \\ 1 & \text{for } \Omega \geq c. \end{cases} \tag{A19}$$

The unconstrained optimum for a fixed level of hedging, c^*, is in the interval $[\mu, \mu + (5/4)\sigma]$, since

$$\frac{1}{10} < 1 - F(c^*) = \frac{\gamma w}{1 - k(a-q) - (1-\gamma)w} < \frac{1}{2}. \tag{A20}$$

from assumptions A2 and A3. We know

$$\lambda_u < \frac{3}{5}\mu, \tag{A21}$$

since from assumption A6, we have for all $c > \mu$

$$\frac{(c-\mu)}{\mu}\gamma w < (1 - a - w - \frac{b}{\mu}) - \frac{2}{5}(1 - a - w) \tag{A22}$$
$$\Rightarrow \frac{b}{\mu} + \frac{(c-\mu)}{\mu}\gamma w < \frac{3}{5}\left(1 - k(a-q) - q - (1-\gamma)w\right) - \gamma w \tag{A23}$$
$$\Leftrightarrow \frac{b + \gamma w c}{\beta_{1u}} < \frac{3}{5}\frac{\beta_{1u}}{\beta_{1u}}\mu \tag{A24}$$
$$\Leftrightarrow \lambda_u < \frac{3}{5}\mu. \tag{A25}$$

Hence the default probability takes the form

$$P := P[CF_\gamma(c, q) < 0 | Y = (1-a)] \tag{A26}$$
$$= P\left[\min(X, c) < \frac{\beta_2}{\beta_{1u}} \middle| Y = (1-a)\right] = F[\lambda_u]. \tag{A27}$$

Let

$$Q := f(\lambda_u)\lambda_u \tag{A28}$$

With

$$\partial_c \lambda_i = \lambda_i \frac{\gamma w}{\beta_2} \tag{A29}$$

$$\partial_q \lambda_i = (-\lambda_i^2)\frac{(k+\delta_i)}{\beta_2} \text{ with } \delta_i = \begin{cases} 1 & \text{for } i = o \\ 0 & \text{for } i = m \\ -1 & \text{for } i = u, \end{cases} \tag{A30}$$

then

$$\partial_q Q = \left[f'(\lambda_u)\lambda_u + f(\lambda_u)\right](\partial_q \lambda_u) \qquad > 0 \tag{A31}$$

$$\partial_c Q = \left[f'(\lambda_u)\lambda_u + f(\lambda_u)\right](\partial_c \lambda_u) \qquad > 0. \tag{A32}$$

Subsequently

$$\partial_c P = f(\lambda_u)(\partial_c \lambda_u) = \frac{\gamma w}{\beta_2} Q \qquad > 0 \tag{A33}$$

$$\partial_q P = f(\lambda_u)(\partial_c \lambda_u) = \frac{(1-k)}{\beta_2}\lambda_u Q \qquad > 0. \tag{A34}$$

Note that

$$\partial_q Q = (\partial_q P)\left[1 + \underbrace{\frac{\mu - \lambda_u}{\sigma}\frac{\lambda_u}{\sigma}}_{=:\tau}\right] = (\partial_q P)(1+\tau) \tag{A35}$$

$$\partial_c Q = (\partial_c P)(1+\tau). \tag{A36}$$

With $\lambda_u < \mu$ from (A21),

$$\partial_c^2 P = \frac{\gamma w}{\beta_2}\left(\partial_c Q - \frac{\gamma w}{\beta_2} Q\right) = \left(\frac{\gamma w}{\beta_2}\right)^2 f'(\lambda_u)\lambda_u^2 \qquad > 0 \tag{A37}$$

$$\partial_c \partial_q P = \frac{\gamma w}{\beta_2}(\partial_q Q) \qquad > 0 \tag{A38}$$

$$\partial_q^2 P = \frac{(1-k)}{\beta_2}\lambda_u \left(2f(\lambda_u) + f'(\lambda_u)\lambda_u\right)(\partial_q \lambda_u) \qquad > 0. \tag{A39}$$

Step 2: There is a smooth function $c^E(q)$ that parameterizes $\{\partial_c E = 0\}$ with $\partial_q c^E > 0$. From the proof of Lemma 1, we know that for any q there exists a unique solution to $\partial_c E = 0$. Since $\partial_q \partial_c E \neq 0$ by (A17) there is a smooth function, $c^E(q)$ that parameterizes $\{\partial_c E = 0\}$ and is uniquely characterized by

$$(\partial_q \partial_c E)(\partial_q c^E) + \partial_c^2 E = 0 \;\Leftrightarrow\; \partial_q c^E = -\frac{\partial_c^2 E}{\partial_q \partial_c E} > 0, \tag{A40}$$

where the inequality follows from (A16) and (A18).

Step 3: There is a smooth function $c^P(q)$ that parameterizes $\{P = \alpha\}$ with $\partial_q c^P < 0$. Since $\partial_q P \neq 0$ by (A34), there is a smooth function, $c^P(q)$, that parameterizes $\{P = \alpha\}$. As above and using (A33) and (A34) for the inequality, it follows that

$$(\partial_q P)(\partial_q c^P) + \partial_c P = 0 \;\Leftrightarrow\; \partial_q c^P = -\frac{\partial_c P}{\partial_q P} < 0. \tag{A41}$$

Step 4: There is a smooth function $c^L(q)$ that parameterizes $\{(\partial_c E)(\partial_q P) - (\partial_q E)(\partial_c P) = 0\}$ with $\partial_q c^L > 0$.
The first order conditions for the Lagrangian associated with the value-at-risk constraint,

$$\mathcal{L} = E[CF] + \lambda\left(P[CF < 0] - t - \alpha\right), \tag{A42}$$

read for non-negative t

$$\begin{align} \partial_c E + \lambda \partial_c P &= 0 \tag{A43}\\ \partial_q E + \lambda \partial_q P &= 0 \tag{A44}\\ P[CF < 0] + t &= \alpha \tag{A45}\\ t\lambda &= 0. \tag{A46}\end{align}$$

For a binding constraint the optimality condition thus reads

$$\frac{\partial_c E}{\partial_q E} = \frac{\partial_c P}{\partial_q P}. \tag{A47}$$

Let

$$L := (\partial_c E)(\partial_q P) - (\partial_q E)(\partial_c P). \tag{A48}$$

Then we have $\partial_c E > 0$ on $\{L = 0\}$, since otherwise $L = (\partial_c E)(\partial_q P) - (\partial_q E)(\partial_c P) < 0$, contradiction. Hence, together with (A16), (A34), (A14), (A38), (A17), (A33), (A15) and (A37) we have

$$\partial_c L = \underbrace{(\partial_c^2 E)}_{<0}\underbrace{(\partial_q P)}_{>0} + \underbrace{(\partial_c E)}_{>0}\underbrace{(\partial_c \partial_q P)}_{>0} - \underbrace{(\partial_c \partial_q E)}_{>0}\underbrace{(\partial_c P)}_{>0} - \underbrace{(\partial_q E)}_{>0}\underbrace{(\partial_c^2 P)}_{>0} \tag{A49}$$

and, additionally with (A39) and (A18),

$$\partial_q L = \underbrace{(\partial_q \partial_c E)}_{>0}\underbrace{(\partial_q P)}_{>0} + \underbrace{(\partial_c E)}_{>0}\underbrace{(\partial_q^2 P)}_{>0} - \underbrace{(\partial_q^2 E)}_{=0}\underbrace{(\partial_c P)}_{>0} - \underbrace{(\partial_q E)}_{>0}\underbrace{(\partial_c \partial_q P)}_{>0}. \tag{A50}$$

We first show

$$\partial_q L > 0 \qquad \text{on} \qquad \{L = 0\}. \tag{A51}$$

From (A50), it suffices to show

$$\begin{align} (\partial_q E)(\partial_c \partial_q P) &< (\partial_c E)(\partial_q^2 P) \tag{A52}\\ \overset{L=0}{\Leftrightarrow} (\partial_c E)\frac{\partial_q P}{\partial_c P}(\partial_c \partial_q P) &< (\partial_c E)(\partial_q^2 P) \tag{A53}\\ \Leftrightarrow (\partial_q P)(\partial_c \partial_q P) &< (\partial_c P)(\partial_q^2 P) \tag{A54}\\ \Leftrightarrow \frac{\gamma w}{\beta_w} Q \frac{1-k}{\beta_2}\lambda_u\left[\lambda_u f'(\lambda_u) + f(\lambda_u)\right](\partial_q \lambda_u) &< \frac{\gamma w}{\beta_2} Q \frac{1-k}{\beta_2}\lambda_u\left[\lambda_u f'(\lambda_u) + 2f(\lambda_u)\right](\partial_q \lambda_u) \tag{A55}\end{align}$$

$$\Leftrightarrow 0 < f(\lambda_u), \tag{A56}$$

which is true.

We now show

$$\partial_c L < 0 \qquad \text{on} \qquad \{L = 0\}. \tag{A57}$$

From (A88) is suffices to show

$$\left[(\partial_c E)(\partial_c \partial_q P) - (\partial_q E)(\partial_c^2 P) + (\partial_c^2 E)(\partial_q P)\right] \frac{(\partial_c P)}{(\partial_c E)} < 0. \tag{A58}$$

Using $L = 0$, i.e., (A47), we have

$$\begin{aligned}
(\partial_c E)(\partial_c \partial_q P) - (\partial_q E)(\partial_c^2 P) &= \frac{(\partial_c E)}{(\partial_c P)} \left[(\partial_c P)(\partial_c \partial_q P) - (\partial_q P)(\partial_c^2 P)\right] && \text{(A59)}\\
&= \frac{(\partial_c E)}{(\partial_c P)} \left(\frac{\gamma w}{\beta_2}\right)^2 \frac{1-k}{\beta_2} f(\lambda_u)^2 \lambda_u^3 && \text{(A60)}
\end{aligned}$$

and

$$\begin{aligned}
(\partial_c^2 E)(\partial_q P) &= \frac{(\partial_c E)}{(\partial_c P)} \frac{(\partial_c^2 E)}{\partial_c E} \left[(\partial_q P)(\partial_c P)\right] && \text{(A61)}\\
&= \frac{(\partial_c E)}{(\partial_c P)} \frac{(-\beta_{1m}) f(c)}{\beta_{1m}(1 - F(c)) - \gamma w} f(\lambda_u) \lambda_u^2 f(\lambda_u) \lambda_u \left(\frac{\gamma w}{\beta_2}\right) \frac{1-k}{\beta_2} && \text{(A62)}\\
&\leq (-1) \frac{(\partial_c E)}{(\partial_c P)} \frac{\gamma w}{\beta_2} \frac{1-k}{\beta_2} f(\lambda_u)^2 \lambda_u^3 \frac{f(c)}{(1 - F(c))}. && \text{(A63)}
\end{aligned}$$

Hence

$$\begin{aligned}
\left[(\partial_c E)(\partial_c \partial_q P) - (\partial_q E)(\partial_c^2 P) + (\partial_c^2 E)(\partial_q P)\right] \frac{(\partial_c P)}{(\partial_c E)} &\leq \frac{1-k}{\beta_2} \frac{\gamma w}{\beta_2} f(\lambda_u)^2 \lambda_u^3 \left[\frac{\gamma w}{\beta_2} - \frac{f(c)}{1 - F(c)}\right] \\
&< 0, && \text{(A64)}
\end{aligned}$$

where the RHS is negative, since the hazard rate $f(c)/(1 - F(c))$ of the normal distribution is increasing on $[\mu, \mu + (5/4)\sigma]$, thus

$$\begin{aligned}
\left[\frac{\gamma w}{\beta_2} - \frac{f(c)}{1 - F(c)}\right] < 0 &\Leftarrow \frac{f(\mu)}{1 - F(\mu)} \geq \frac{\gamma w}{\gamma w \mu + b} && \text{(A65)}\\
&\Leftrightarrow \sqrt{\frac{2}{\pi}} \frac{1}{\sigma} \geq \frac{\gamma w}{\gamma w \mu + b} && \text{(A66)}\\
&\Leftrightarrow b \geq \gamma w \left[\sqrt{\frac{\pi}{2}} \sigma - \mu\right], && \text{(A67)}
\end{aligned}$$

which holds since the expression in brackets is negative from assumption A1.

Since $\partial_q L \neq 0$, there is a smooth function, $c^L(q)$, that parameterizes $\{(\partial_c E)(\partial_q P) - (\partial_q E)(\partial_c P) = 0\}$. Using (A51) and (A57), we have

$$(\partial_q L)(\partial_q c^L) + \partial_c L = 0 \;\Leftrightarrow\; \partial_q c^L = -\frac{\partial_c L}{\partial_q L} > 0. \tag{A68}$$

Step 5: Unique solution which is one of four cases.
Since $\partial_q c^E > 0$ and $\partial_q c^P < 0$, as shown in step 2 and 4, there is at most one intersection between $\{P = \alpha\}$ and $\{\partial_c E = 0\}$. Likewise, since $\partial_q c^L > 0$ and $\partial_q c^P < 0$, as shown in step 3 and 4, there is at most one intersection between $\{P = \alpha\}$ and $\{L = 0\}$. Also, as we have shown in the proof that $\{L = 0\} \subset \{\partial_c E > 0\}$, so we have $c^L < c^E$. Hence, there are four cases

a) There is no intersection between c^E and c^P and $\{\partial_c E = 0\} \subset \{P < \alpha\}$. Then the unconstrained optimal solution is feasible and therefore chosen.

b) There exists an intersection between c^E and c^P, but none between c^L and c^P. Then $\{L = 0\} \subset \{P < \alpha\}$, since otherwise $\{L = 0\} \subset \{P > \alpha\}$. But since $c^L < c^E$ this would imply $\{\partial_c E = 0\} \subset \{P > \alpha\}$, contradiction. Hence, since there is no intersection between c^L and c^P, there is no internal optimum on the range of optimization $\{\partial_c E \geq 0\} \cap \{P \leq \alpha\}$. But then, since $\partial_c E > 0$ and $\partial_q E > 0$, the firm chooses the point on the constraint with no hedging. The same is true if there is neither an intersection between c^L and c^P nor an intersection between c^E and c^P, and $\{\partial_c E = 0\} \subset \{P > \alpha\}$.

c) There is an intersection between c^L and c^P. Then the solution is the constrained solution, since it is the (internal) optimum.

d) There is neither an intersection between c^L and c^P nor an intersection between c^E and c^P and $\{L = 0\} \subset \{P > \alpha\}$. Then the firm chooses the point on the constraint with most hedging (if such a point still yields positive profits - otherwise the case is not of interest, since there is no feasible profitable solution at all).

$\square$

A3 Proof of Proposition 2

For ease of notation, we omit the subscript for λ and take λ to be λ_u, and omit the subscript for β_1 and take $\beta_1 = \beta_{1m}$. As before in the proofs, we consider the amplitude of the partially hedged exchange rate $q := a - h$, instead of h.

Step 1: Further preliminary properties.
We have

$$\partial_\gamma \partial_c E = (\partial_\gamma \beta_1)(1 - F(c)) - w = -wF(c) \quad < 0 \tag{A69}$$
$$\partial_\gamma \partial_q E = k(\partial_\gamma E[\min(X, c)]) \quad = 0. \tag{A70}$$

With

$$\partial_\gamma \lambda = \frac{w}{\beta_2} \lambda (c - \lambda). \tag{A71}$$

also

$$\partial_\gamma P = f(\lambda)(\partial_\gamma \lambda) = \frac{w}{\beta_2}(c - \lambda) Q \quad > 0 \tag{A72}$$
$$\partial_\gamma \partial_q P = \frac{1-k}{\beta_2} \left[\partial_\gamma (\lambda Q) - \frac{wc}{\beta_2} (\lambda Q) \right] \tag{A73}$$
$$= \frac{1-k}{\beta_2} \left[\lambda (\partial_\gamma Q) - \frac{\lambda w}{\beta_2} (\lambda Q) \right] \tag{A74}$$

$$= \frac{1-k}{\beta_2}\left[\lambda(1+\tau)(\partial_\gamma P) - \underbrace{\frac{w}{\beta_2}(c-\lambda)Q}_{\partial_\gamma P}\lambda\frac{\lambda}{(c-\lambda)}\right] \tag{A75}$$

$$= \frac{1-k}{\beta_2}\lambda\left[(1+\tau) - \frac{\lambda}{(c-\lambda)}\right](\partial_\gamma P) \tag{A76}$$

$$\partial_\gamma\partial_c P = \frac{w}{\beta_2}\left[\gamma\partial_\gamma Q + \left(1 - \frac{\gamma w c}{\beta_2}\right)Q\right] \tag{A77}$$

$$= \frac{w}{\beta_2}\left[\gamma(1+\tau) + \frac{b}{w}\frac{1}{(c-\lambda)}\right](\partial_\gamma P). \tag{A78}$$

Rearranging (A37) yields

$$\partial_c^2 P = \frac{\gamma w}{\beta_2}\left(\partial_c Q - \frac{\gamma w}{\beta_2}Q\right) \tag{A79}$$

$$= \frac{\gamma w}{\beta_2}(\partial_c P)(1+\tau) - \left(\frac{\gamma w}{\beta_2}\right)^2 Q \tag{A80}$$

$$= \frac{\gamma w}{\beta_2}(1+\tau)(\partial_q P)\frac{(\partial_c P)}{(\partial_q P)} - \frac{\gamma w}{\beta_2}(\partial_c P) \tag{A81}$$

$$= \frac{\gamma w}{\beta_2}(1+\tau)\frac{\gamma w}{1-k}\frac{1}{\lambda}(\partial_q P) - \frac{\gamma w}{\beta_2}(\partial_c P). \tag{A82}$$

We have

$$\partial_\gamma L = \underbrace{(\partial_\gamma\partial_c E)}_{<0}\underbrace{(\partial_q P)}_{>0} + \underbrace{(\partial_c E)}_{>0}(\partial_\gamma\partial_q P) - \underbrace{(\partial_\gamma\partial_q E)}_{=0}\underbrace{(\partial_c P)}_{>0} - \underbrace{(\partial_q E)}_{>0}\underbrace{(\partial_\gamma\partial_c P)}_{>0} \tag{A83}$$

$$= (\partial_\gamma\partial_c E)(\partial_q P) + Z \tag{A84}$$

with

$$\begin{aligned}
Z &:= (\partial_c E)(\partial_\gamma\partial_q P) - (\partial_q E)(\partial_\gamma\partial_c P) \\
&= (\partial_c E)\frac{1-k}{\beta_2}\lambda\left[(1+\tau) - \frac{\lambda}{(c-\lambda)}\right](\partial_\gamma P) - (\partial_q E)\frac{\gamma w}{\beta_2}\left[(1+\tau) + \frac{b}{\gamma w}\frac{1}{(c-\lambda)}\right](\partial_\gamma P) \\
&= (\partial_\gamma P)\frac{(1-k)}{\gamma w}\left[(\partial_c E)(1+\tau)\frac{\gamma w}{\beta_2} - (\partial_q E)(1+\tau)\frac{\gamma w}{\beta_2}\frac{\gamma w}{(1-k)}\right] \\
&\qquad + (\partial_\gamma P)\left[-\frac{\lambda^2}{(c-\lambda)}\frac{(1-k)}{\beta_2}(\partial_c E) + (\partial_q E)\frac{b}{\beta_2}\frac{1}{(c-\lambda)}\right] \\
&= (\partial_\gamma P)\frac{(1-k)}{\gamma w}\lambda G + (\partial_\gamma P)\left[-(\partial_q E)\frac{\gamma w}{\beta_2} + k(1-F_c) - \frac{\lambda^2}{(c-\lambda)}\frac{1-k}{\beta_2}(\partial_c E) + (\partial_q E)\frac{b}{\beta_2}\frac{1}{(c-\lambda)}\right] \\
&= \left[G\lambda\frac{(1-k)}{\gamma w}\right](\partial_\gamma P) + H(\partial_\gamma P)
\end{aligned}$$

with

$$G := \frac{1}{\lambda}\left[(\partial_c E)(1+\tau)\frac{\gamma w}{\beta_2}\lambda - k(1-F_c)\frac{\gamma w}{1-k} - (\partial_q E)\tau\frac{\gamma w}{\beta_2}\frac{\gamma w}{1-k}\right] \tag{A85}$$

and

$$H := k(1-F_c) - (\partial_c E)\frac{\lambda^2}{(c-\lambda)}\frac{(1-k)}{\beta_2} - (\partial_q E)\frac{\gamma w}{\beta_2}\left(1+\frac{b}{\gamma w(c-\lambda)}\right). \tag{A86}$$

At the same time for $\partial_c L$, we have with (A88)

$$\partial_c L = (\partial_c^2 E)(\partial_q P) + N \tag{A87}$$

with

$$\begin{aligned}
N &:= (\partial_c E)(\partial_c\partial_q P) - (\partial_q E)(\partial_c^2 P) - (\partial_c\partial_q E)(\partial_c P)\\
&= (\partial_c E)\frac{\gamma w}{\beta_2}(1+\tau)(\partial_q P) - (\partial_q E)\left[(\partial_q P)\frac{\gamma w}{\beta_2}\frac{\gamma w}{1-k}(1+\tau)\frac{1}{\lambda} - \frac{\gamma w}{\beta_2}(\partial_c P)\right] - k(1-F_c)(\partial_q P)\frac{\partial_c P}{\partial_q P}\\
&= \left[(\partial_c E)(1+\tau)\frac{\gamma w}{\beta_2}\lambda - (\partial_q E)(1+\tau)\frac{\gamma w}{\beta_w}\frac{\gamma w}{(1-k)} + (\partial_q E)\frac{\gamma w}{\beta_2}\frac{\gamma w}{(1-k)} - k(1-F_c)\frac{\gamma w}{(1-k)}\right]\frac{\partial_q P}{\lambda}\\
&= \frac{1}{\lambda}\left[(\partial_c E)(1+\tau)\frac{\gamma w}{\beta_2}\lambda - (\partial_q E)\tau\frac{\gamma w}{\beta_w}\frac{\gamma w}{(1-k)} - k(1-F_c)\frac{\gamma w}{(1-k)}\right](\partial_q P)\\
&= G(\partial_q P).
\end{aligned}$$

Hence,

$$\begin{aligned}
\partial_c L &= \left[(\partial_c^2 E) + G\right](\partial_q P) &\text{(A88)}\\
&=: \tilde{G}(\partial_q P). &\text{(A89)}
\end{aligned}$$

Step 2: $\partial_\gamma c^L < 0$ on $\{L=0\}$, $\partial_\gamma c^E < 0$ and $\partial_\gamma c^P < 0$.
By definition of c^E, we have $\partial_c E(\gamma, c^E(\gamma)) = 0$, hence

$$\partial_\gamma\partial_c E + (\partial_c^2 E)(\partial_\gamma c^E) = 0 \overset{\text{(A69),(A16)}}{\Rightarrow} \partial_\gamma c^E = -\frac{\partial_\gamma\partial_c E}{\partial_c^2 E} < 0. \tag{A90}$$

Likewise,

$$\partial_\gamma P + (\partial_c P)(\partial_\gamma c^P) = 0 \overset{\text{(A72),(A33)}}{\Rightarrow} \partial_\gamma c^P = -\frac{\partial_\gamma P}{\partial_c P} < 0. \tag{A91}$$

Likewise, from (A57) and (A51) we have

$$\partial_\gamma L + (\partial_c L)(\partial_\gamma c^L) = 0 \;\Leftrightarrow\; \partial_\gamma c^L = -\frac{\partial_\gamma L}{\partial_c L} < 0 \quad \text{on} \quad \{L=0\}. \tag{A92}$$

Step 3: $|\partial_\gamma c^L| < |\partial_\gamma c^P|$ and $|\partial_\gamma c^E| < |\partial_\gamma c^P|$.
From (A88) and (A84), we have

$$\begin{aligned}
\partial_\gamma L &= (\partial_\gamma\partial_c E)(\partial_q P) + Z &\text{(A93)}\\
&= (\partial_\gamma\partial_c E)(\partial_q P) + \left[\tilde{G}\lambda\frac{(1-k)}{\gamma w}\right](\partial_\gamma P) + H(\partial_\gamma P) - (\partial_c^2 E)\lambda\frac{(1-k)}{\gamma w}(\partial_\gamma P) &\text{(A94)}\\
&= \tilde{G}\frac{(\partial_q P)}{(\partial_c P)}(\partial_\gamma P) + H(\partial_\gamma P) + \underbrace{\left[(\partial_\gamma\partial_c E)\frac{\partial_q P}{\partial_\gamma P} - (\partial_c^2 E)\lambda\frac{(1-k)}{\gamma w}\right]}_{:=R}(\partial_\gamma P) &\text{(A95)}
\end{aligned}$$

$$= \partial_c L \frac{(\partial_\gamma P)}{(\partial_c P)} + (H+R)(\partial_\gamma P), \tag{A96}$$

with

$$R = (\partial_\gamma \partial_c E) \frac{\partial_q P}{\partial_\gamma P} - (\partial_c^2 E) \lambda \frac{(1-k)}{\gamma w} \tag{A97}$$

$$= (\partial_\gamma \partial_c E) \frac{\partial_q P}{\partial_\gamma P} - (\partial_c^2 E) \frac{\partial_q P}{\partial_c P}. \tag{A98}$$

Hence,

$$-\partial_\gamma c^L = \frac{\partial_\gamma L}{\partial_c L} = \frac{\partial_\gamma P}{\partial_c P} + \frac{(H+R)(\partial_\gamma P)}{(\partial_c L)} = -\partial_\gamma c^P + (H+R) \underbrace{\frac{(\partial_\gamma P)}{(\partial_c L)}}_{<0 \text{ on } \{L=0\}}, \tag{A99}$$

and from step 2 and on $\{L = 0\}$

$$|\partial_\gamma c^L| < |\partial_\gamma c^P| \Leftrightarrow -\partial_\gamma c^L < -\partial_\gamma c^P \Leftrightarrow (H+R) > 0. \tag{A100}$$

Similarly,

$$-\partial_\gamma c^E = \frac{(\partial_\gamma \partial_c E)}{(\partial_c^2 E)} = \frac{\partial_\gamma P}{\partial_c P} + \frac{(\partial_c \partial_\gamma E) - (\partial_\gamma P)/(\partial_c P)(\partial_c^2 E)}{(\partial_c^2 E)} = -\partial_\gamma c^P + R \underbrace{\frac{(\partial_\gamma P)}{(\partial_c^2 E)(\partial_q P)}}_{<0}, \tag{A101}$$

and from step 2

$$|\partial_\gamma c^E| < |\partial_\gamma c^P| \Leftrightarrow -\partial_\gamma c^E < -\partial_\gamma c^P \Leftrightarrow R > 0. \tag{A102}$$

It remains to show $R > 0$ and $(H + R) > 0$.

Claim: $R > 0$.

Proof of claim.

$$R = (\partial_\gamma \partial_c E) \frac{\partial_q P}{\partial_\gamma P} - (\partial_c^2 E) \frac{\partial_q P}{\partial_c P} \tag{A103}$$

$$= -F_c(1-k) \frac{\lambda}{(c-\lambda)} + \beta_1 f_c \frac{(1-k)}{\gamma w} \lambda \tag{A104}$$

$$= \frac{(1-k)\lambda}{(1-F_c)} \Big[-\frac{F_c(1-F_c)}{(c-\lambda)} + \underbrace{\frac{\beta_1}{\gamma w}(1-F_c)}_{>1 \text{ since } \partial_c E > 0} f_c \Big] \tag{A105}$$

$$\geq \frac{(1-k)\lambda}{(1-F_c)} \Big[-\frac{1}{4(c-\lambda)} + f_c \Big] \tag{A106}$$

From (A21), assumption A2 and A1, we have

$$(c-\lambda) > c - \frac{3}{5}\mu > \frac{2}{5}\mu > 2\sigma. \tag{A107}$$

From assumption A3, we know $c < \mu + (5/4)\sigma$, hence $f_c > 1/(8\sigma)$. Plugged into (A106), this yields $R > 0$.

Claim: $(H + R) > 0$.

Proof of claim. From (A21) we have $(c - \lambda) > (1/3)c$, hence

$$1 + \frac{b}{\gamma w(c-\lambda)} \leq \frac{\gamma w + 3b/c}{\gamma w} \leq \frac{3\beta_2/c}{\gamma w}. \tag{A108}$$

Thus, we have

$$\begin{aligned}
H + R &\geq k(1-F_c) - \left[(\partial_c E)\frac{\lambda^2(1-k)}{(c-\lambda)\beta_2} + (\partial_q E)\frac{3}{c}\right] + \frac{(1-k)\lambda}{(1-F_c)}\left[-\frac{F_c(1-F_c)}{(c-\lambda)} + \frac{\beta_1}{\gamma w}(1-F_c)f_c\right] \\
&\geq k\left[(1-F_c) - 3\frac{E[\min(X,c)]}{c}\right] + \frac{(1-k)\lambda}{(1-F_c)}\left[-\frac{F_c(1-F_c)}{(c-\lambda)} + f_c - \frac{\lambda(1-F_c)}{(c-\lambda)\beta_2}(\partial_c E)\right] \\
&\geq -3k + \frac{(1-k)\lambda}{(1-F_c)}\Bigg[-\frac{(1-F_c)}{(c-\lambda)}\underbrace{[F_c + \frac{\lambda}{\beta_2}(\partial_c E)]}_{\leq \lambda/\beta_2(\beta_1 - \gamma w)} + f_c\Bigg] \\
&\geq -3k + (1-k)\lambda\left[\frac{f_c}{(1-F_c)} - \frac{\lambda}{(c-\lambda)}\frac{1}{\beta_2}(\beta_1 - \gamma w)\right]
\end{aligned}$$

Since the hazard rate is increasing for $c \geq \mu$ and

$$\frac{f_\mu}{(1-F_\mu)} = \sqrt{\frac{2}{\pi}}\frac{1}{\sigma} \approx 0.79\frac{1}{\sigma} \geq \frac{3}{4}\frac{1}{\sigma}, \tag{A109}$$

the expression in brackets is positive if

$$\frac{\lambda}{(c-\lambda)}\frac{1}{\beta_2}(\beta_1 - \gamma w) \leq \frac{3}{4}\frac{1}{\sigma} \tag{A110}$$

$$\Leftrightarrow \frac{(\beta_1 - \gamma w)}{(\beta_1 - q)}\frac{3}{4}\sigma \leq (c - \lambda). \tag{A111}$$

But $(c - \lambda) \geq 2\sigma$, hence,

$$\frac{(\beta_1 - \gamma w)}{(\beta_1 - q)}\frac{3}{4} \leq 2 \Leftrightarrow \frac{q}{w} - \gamma \leq \frac{(\beta_1 - \gamma w)}{3w}, \tag{A112}$$

is sufficient for the expression in brackets to be positive. This is ensured by assumptions A4 and A3, since then

$$a \leq \frac{4}{9}(1-w) - \frac{1}{3}kh_{max} \tag{A113}$$

$$\Leftrightarrow a \leq \frac{1}{9}(1-w) + \frac{1}{3}(1 - w - kh_{max}) \tag{A114}$$

$$\Rightarrow \bar{\gamma}_{\min} \geq \frac{a}{w} - \frac{(\beta_1 - \gamma w)}{3w}. \tag{A115}$$

From (A109), the expression in brackets can be bounded from below by $(\sqrt{2/\pi} - 3/4)(1/\sigma)$. With $\lambda \geq 1$, assumption A5 then ensures $H + R > 0$.

Step 4: The values of γ that lead to case c) are one interval in $[\gamma_{min}, \gamma_{max}]$.

Let

$$\mathbb{D} := \left\{(\gamma, q, c) | \gamma \in [\gamma_{min}, \gamma_{max}], q \in [q_{min}, a], c \in \mathbb{R}^+\right\} =: \mathbb{D}_1 \times \mathbb{D}_2 \times \mathbb{D}_3 \tag{A116}$$

and consider E and P as functions on $\mathbb{D}$, subsequently also $L = (\partial_c E)(\partial_q E) - (\partial_q E)(\partial_c P)$. Define

$$\mathbb{C}^{LP} := \{L = 0\} \cap \{P = \alpha\}. \tag{A117}$$

$\mathbb{C}^{LP}$ is a smooth submanifold of dimension 1 of $\mathbb{D}$ if everywhere on $\mathbb{C}^{LP}$

$$rank \begin{pmatrix} DL \\ DP \end{pmatrix} = 2. \tag{A118}$$

This is indeed the case since on $\{L = 0\}$

$$\det \begin{pmatrix} \partial_c L & \partial_q L \\ \partial_c P & \partial_q P \end{pmatrix} = (\partial_c L)(\partial_q P) - (\partial_q L)(\partial_c L) < 0. \tag{A119}$$

Hence, for all $x \in \mathbb{C}^{LP}$ one can locally parameterize $\mathbb{C}^{LP}$ via γ. Since from Proposition 1, for each γ, there is at most one (q, c) such that $(\gamma, q, c) \in \mathbb{C}^{LP}$, there is an open subset $I^{LP} \subset [\gamma_{min}, \gamma_{max}]$ such that some $g^{LP} : I^{LP} \to \mathbb{D}^0$ (interior of $\mathbb{D}$) globally parameterizes $\mathbb{C}^{LP} \cap \mathbb{D}^0$ with $g^{LP}(\gamma) = (q^{LP}(\gamma), c^{LP}(\gamma))$.

$\mathbb{C}^{LP}$ is closed in $\mathbb{D}$ and for some large c also bounded on $\mathbb{D}_1 \times \mathbb{D}_2 \times [0, c]$, hence compact. Thus, the boundary of $\mathbb{C}^{LP}$ needs to lie on the boundary of $\mathbb{D}$, hence in

$$\{\gamma_{min}, \gamma_{max}\} \times \mathbb{D}_2 \times \mathbb{D}_3 \quad \cup \quad \mathbb{D}_1 \times \{q_{min}, a\} \times \mathbb{D}_3. \tag{A120}$$

It remains to show that I^{LP} consists of only one interval. For this it suffices to show that $\partial_\gamma q^{LP} < 0$. If I^{LP} consisted of multiple intervals, there were $x_1, x_2 \in \mathbb{C}^{LP}$ with $\partial_\gamma q^{LP}(x_1) < 0 < \partial_\gamma q^{LP}(x_2)$. (Loosely speaking, if there was a gap in I^{LP}, i.e. $\gamma_1 < \gamma_2 < \gamma_3$ such that $\gamma_1, \gamma_3 \in I^{LP}$, but $\gamma_2 \notin I^{LP}$, then $q^{LP}(\gamma_2) \in \{q_{min}, a\}$, hence either bigger or smaller than both $q^{LP}(\gamma_1), q^{LP}(\gamma_3) \in (q_{min}, a)$. Hence, in the first case, $\partial_\gamma q^{LP} < 0$ for some $\gamma > \gamma_1$ and $\partial_\gamma q^{LP} > 0$ for some $\gamma < \gamma_3$.)

Claim: $\partial_\gamma q^{LP} < 0$.

Proof of claim. For some γ_1, consider the plane $\{\gamma_1\} \times \mathbb{D}_1 \times \mathbb{D}_2$ and the corresponding point therein in $\mathbb{C}^{LP}$, namely $(q^{LP}(\gamma_1), c^L(\gamma_1, q^{LP}(\gamma_1)))$. By definition, $c^L(\gamma_1, q^{LP}(\gamma_1)) = c^P(\gamma_1, q^{LP}(\gamma_1))$. For some small $\varepsilon > 0$ consider the plane $\{\gamma_2 = \gamma_1 + \varepsilon\} \times \mathbb{D}_1 \times \mathbb{D}_2$ at the previous level of q, $q^{LP}(\gamma_1)$. Then,

$$\begin{aligned} c^P(\gamma_2, q^{LP}(\gamma_1)) \approx c^P(\gamma_1, q^{LP}(\gamma_1)) + \varepsilon \partial_\gamma c^P &= c^L(\gamma_1, q^{LP}(\gamma_1)) + \varepsilon \partial_\gamma c^P \\ &< c^L(\gamma_1, q^{LP}(\gamma_1)) + \varepsilon \partial_\gamma c^L \approx c^L(\gamma_2, q^{LP}(\gamma_1)), \end{aligned} \tag{A121}$$

since by step 3, $\partial_\gamma c^L > \partial_\gamma c^P$. Since $\partial_q c^P < 0$ and $\partial_q c^L > 0$, the point in $\mathbb{C}^{LP}$ in $\{\gamma_2\} \times \mathbb{D}_1 \times \mathbb{D}_2$ needs to have $q^{LP}(\gamma_2) < q^{LP}(\gamma_1)$. Hence, $\partial_\gamma q^{LP} < 0$.

Step 5: The values of γ that lead to case b) are one interval in $[\gamma_{min}, \gamma_{max}]$.
For γ in case b) we already know that $q = a$ and that $c^P(\gamma, a) < c^E(\gamma, a)$. From step 3 we have $\partial_\gamma c^E > \partial_\gamma c^P$. Hence, c^E can cross c^P at most once.

B Appendix: Data Appendix

B1 Cleaning BTR KUG

In BTR KUG, we create STW spells, i.e., periods of STW usage with a maximal gap of two months and transform the data into a monthly panel. We match this unbalanced panel at the establishment-month level to the Establishment History Panel (BHP) which we have previously expanded to the monthly level.

We drop all establishments that are in a special construction scheme *(Baugewerbetarif)* at any point in time (around 5% of observation in the initial BTR KUG). We also drop establishments that in some year appear in BTR KUG, but not in BHP, except when this happens in the year that marks the establishment's last (first) appearance in BHP. Since BHP is based on establishments with at least one employee subject to social insurance contributions on June 30 of each year, such cases can occur if an establishment closes before June 30, but used STW in earlier months that year.

B2 Cleaning Dafne

Before merging firm financial information from Dafne to the employment data at the IAB, we clean Dafne as follows with the resulting number of firms per step given in parenthesis. Starting point are firms that report an income statement in 2019 *(48,000)* at the unconsolidated level. We further restrict attention to firms that report revenues in 2019 and 2020 *(21,000).* Among the firms that report at the consolidated and unconsolidated level (i.e., group heads) we restrict attention to firms that are likely not just holdings. In particular, we demand a) that firms have more than 10 employees at the unconsolidated level in 2019 and 2020 (if reported) and b) that firms' unconsolidated revenues are at least 10% of consolidated revenues between 2016 and 2020 (if consolidated revenues are available) *(17,800).*

Similar to the standard data cleaning methodology for ORBIS (Kalemli-Ozcan, Sorensen, Villegas-Sanchez, Volosovych, and Yesiltas, 2015), we discard firms that do not pass basic data consistency checks on their key financials (whenever assets are available they are positive, equity exceeds assets in 2019 and 2020, fixed assets are never negative, revenues are never negative, sales-to-asset ratio is below the 99.9 percentile (pooled across all years), assets to not exceed those of VW, fixed asset-to-asset ratio below 1) *(17,200).* We demand that information on cash flow, cash and equity is available in 2019 *(16,400).*

We consolidate information on FX gains and FX losses across two accounting formats (*Umsatzkostenverfahren* and *Gesamtkostenverfahren*) and two FX reporting schemes (*Aufwendungen/ Erträge aus Währungsumrechnung*, *Währungsgewinne/ Währungsverluste*). We identify which of the two FX schemes is the predominant one at the firm level (i.e., which one appears more often than the other). We consolidate information on currency gains and on currency losses across the two FX schemes, as the same information in annual reports is collected inconsistently across both schemes. Here, we take the predominant FX scheme. If information on gains is missing in the predominant FX scheme, but available in the other format, we add the information from the other (analogously for losses). If only gains or only losses are reported, we set the other to zero.

B3 Details on the Relative Wage Bill Gap

BTR KUG contains the monthly number of short-time workers and information on the relative wage bill gap among them. The gap is defined as the gap in wages among short-time workers divided by the regular wage bill of short-time workers. Is it available in buckets: for values below 0.25 it takes value 0.175, for values in $(0.25, 0.5]$ it takes value 0.375, for values in $(0.5, 0.75]$ it takes value 0.625, for values in $(0.75, 0.99]$ it takes value 0.87, and it takes value 1 for values above 0.99.

For a subsample of establishments that use STW in 2020, we have individual-level information on the wage gap. We aggregate this individual-level information to the establishment level and confirm that it aligns well with the described bucketed variable.

B4 Keyword-Based Classification of Derivatives Use (Firms' Reports)

We have manually downloaded annual reports for 28,495 firm-year observations. Firms are required to include information on their risk management in the appendix of annual reports, and we conduct a text analysis to identify mentions of FX hedging instruments. The reports are in German.

1) We extract the name of the company and year from the report.

2) We search for explicit mentions of words indicating FX hedging. Specifically, as first pattern, we search for the word "FX forward" or "FX option" (*Devisentermin, Devisenoption, Devisenswap*), and, as second pattern, for other words related to FX hedging (*Währungssicherung, Währungsabsicherung, Kurrsicherung, Devisenabsicherung, kursgesichert*).

3) We count raw occurrences of each pattern. Aditionally, we check if a pattern occurs in combination with words suggesting negation (*keine, nicht durch, bestehen nicht, bestanden nicht, verzichtet*), or in combination with words that suggest a conditional sentence structure like "If foreign exchange hedges exist, we use xyz accounting ..." (*sofern, soweit, falls*).

4) For each pattern, we classify for each year the occurrence structure as "No mention" (assigned value 0, pattern not found), "Only negated mentions" (assigned value 1, pattern only occurs in combination with words that suggest negation), "Sentences with mentions all conditional" (assigned value 2, pattern only occurs in combination with words that suggest a conditional sentence), "Partially negated mentions" (assigned value 3, not all mentions occur in a combination with a word that suggests negation) and "Hedges" (assigned value 4, none of the above). The following table shows the resulting classification.

	Pattern 1		Pattern 2	
	Percent	N	Percent	N
No mention	77.15%	21,983	86.40%	24,621
Only negated mentions	0.71%	203	0.73%	207
Sentences with mentions all conditional	0.34%	97	0.96%	274
Partially negated mentions	0.96%	274	0.33%	94
Hedges	20.84%	5,939	11.58%	3,299
Sum	100%	28,495	100%	28,495

5) We use the highest classification across the two patterns (*combined classification value*), except when one pattern has only negated mentions in which case we set the combined classification value to 1.

6) We classify a firm as using FX derivatives in a year if the combined classification value is at least two. Thus, a non-user is a firm that either does not mention or explicitly negates the usage of FX derivatives.

B5 AI-based Classification of Active FX Management (Firms' Reports)

We have manually downloaded annual reports for 4,613 firms in 2019.

1) We identify the passage on risk management in the appendices of annual reports based on headers that include variants of the word "risk report" (*Risikobericht*, *Chancen und Risiken*, ...).

2) We extract the first and subsequent page on which it occurs (*risk passage*).

3) We use ChatGPT (batch; gpt-4o-mini; September 12, 2024) per risk passage with the following prompt (original in German; translated): "Does the firm actively manage its FX risk? Answer with Yes, No or No Info, and cite the five most relevant sentences on FX-risk management from the risk passage provided."

We manually classify the hedging strategies for random subset of the firms that the AI classified as actively hedging FX risk. This manual classification also serves as a quality check for the keyword-based measure. Among the 68 firms manually classified as derivatives users, the classification coincides in 76% of cases with the keyword-based approach. However, of the 67 firms identified as derivatives users by the keyword-based approach 22% were not classified as such manually. This discrepancy arises from the annual reports' flexible format: the keyword-based method misses formulations outside the predefined word set, whereas the manual classification only relies on the risk-management section in annual reports for feasibility. However, some firms do not report FX-derivatives usage in the risk passage but do report it elsewhere.

B6 Keyword-Based Classification of FX Service Provision (Banks' Reports)

We have manually downloaded annual reports for 7,360 bank-year observations. We compile information on outstanding FX derivatives, as banks are required to include this information in the appendices of their annual reports.

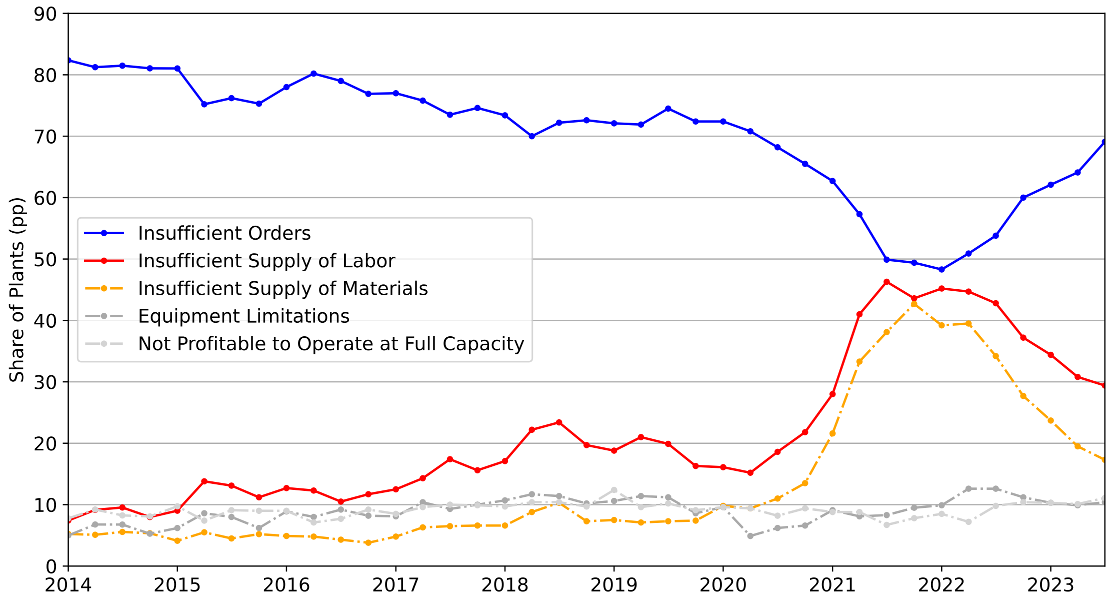
1) The starting point are relationship banks of firms in Dafne with FX transaction income data and a revenue change from 2019 to 2020 in the range of $[-20\%, 20\%]$.

2) These banks are matched by name to institutions in SNL Fundamentals (accessed via WRDS). The matched sample consists of 745 banks, including 321 savings banks (*Sparkassen*), 345 cooperative banks (*Volksbanken*), three major banks (*Deutsche Bank, Commerzbank, Unicredit*) and 65 other.

3) We extract annual information on outstanding FX derivatives from tables of varying format within pdfs.

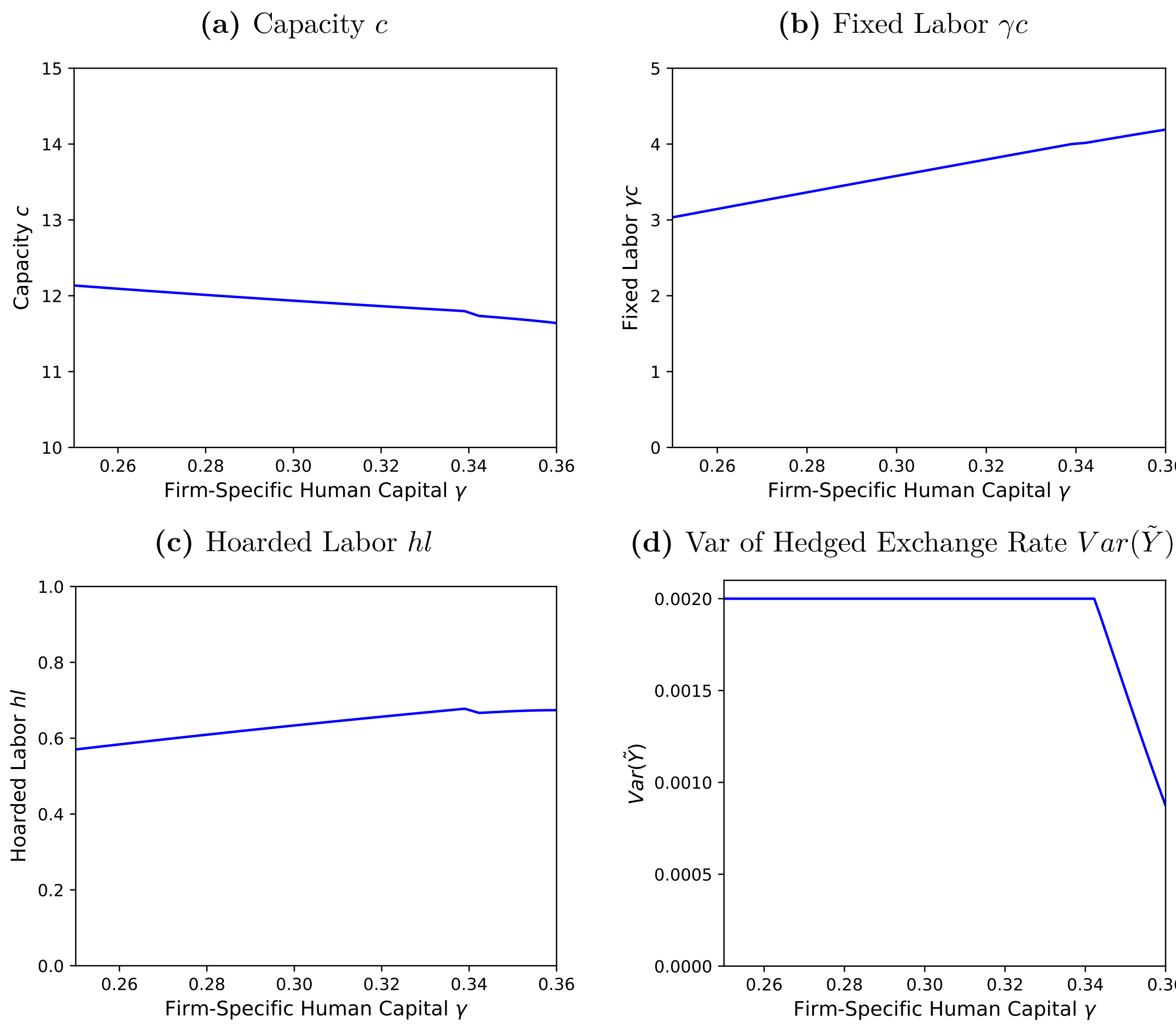
C Supplementary Figures

Figure C.1: Most Frequent Reasons Why Production Is Below Full Production Capability



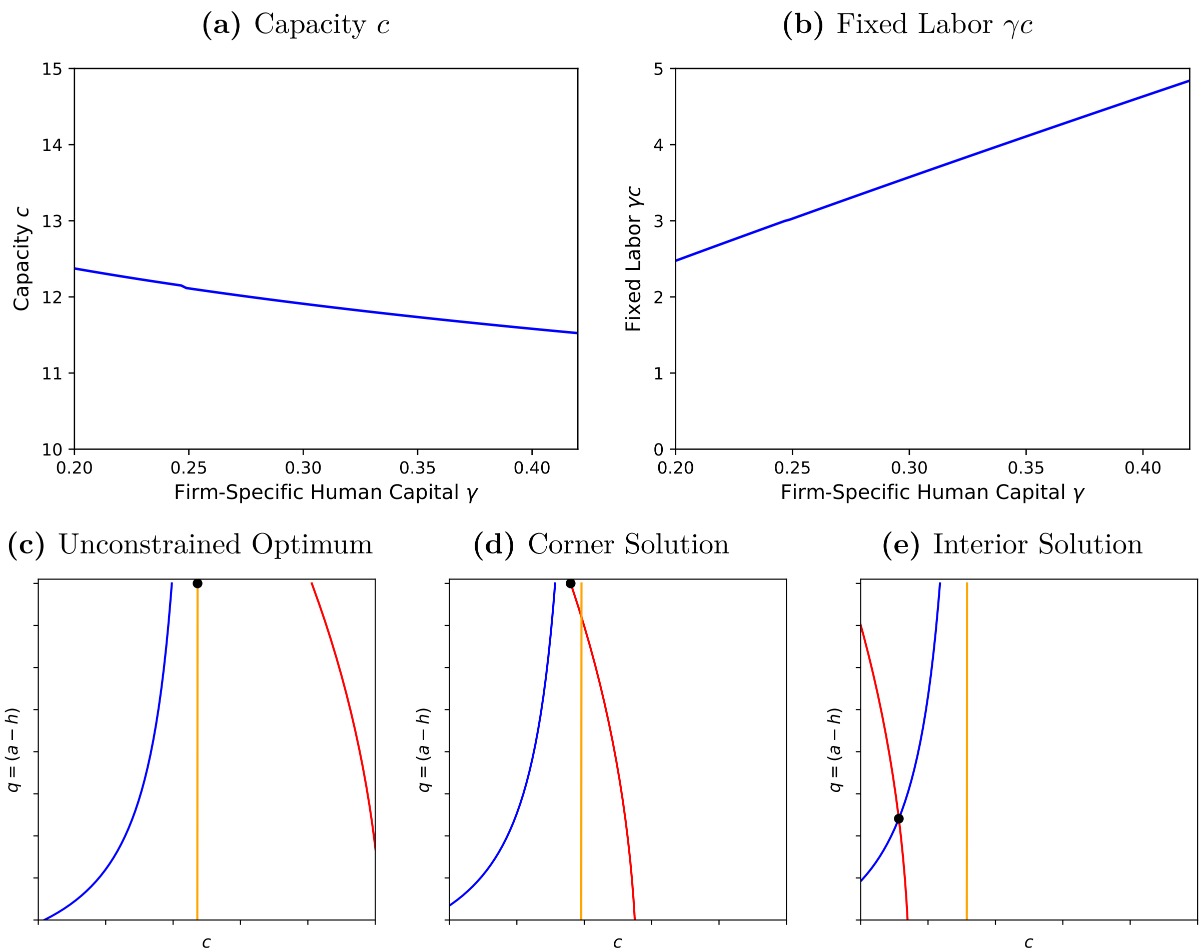
Notes: The figure shows the share of plants, among those with reduced production, that indicate each reason as a primary reason for actual production being below full production capability. The data is quarterly. Multiple answers are possible. The data source is the Quarterly Survey of Plant Capacity Utilization (QSPC) from the US Census Bureau.

Figure C.2: Model: Solution with Alternative Constraint



Notes: This figure shows how optimal *capacity*, c, in Panel (a), optimal *fixed labor*, γc, in Panel (b), optimal *hoarded labor*, $hl = \gamma(c - E[\min(X, c)])$, in Panel (c), and, the optimal *variance of the hedged exchange rate*, $Var(\tilde{Y}) = 2p(a-h)^2$ in Panel (d) change as a function of firm-specific human capital γ. The constraint considered is $P[CF < 0] < \alpha$. The model is numerically solved for the following set of parameters: $\mu = 10, \sigma = 2, b = 2, a = 0.1, p = 0.1, w = 0.4, \alpha = 0.006, k = 0.005, q_{min} = 0.02$.

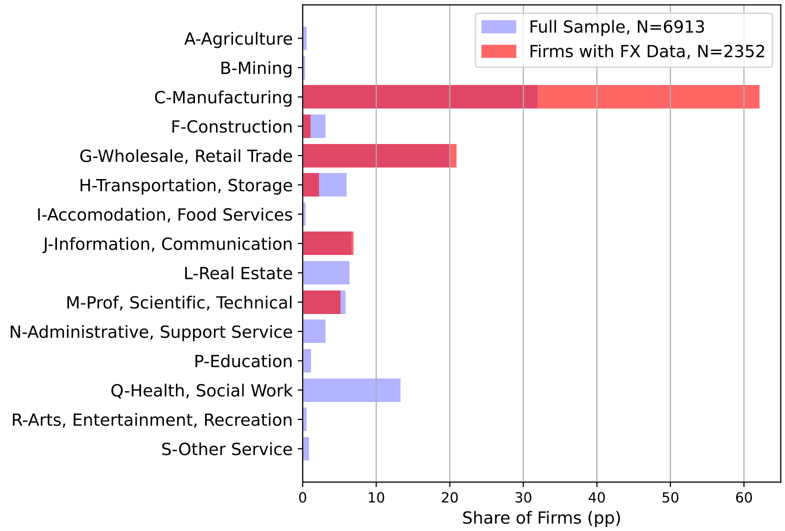
Figure C.3: Model: Further Illustrations



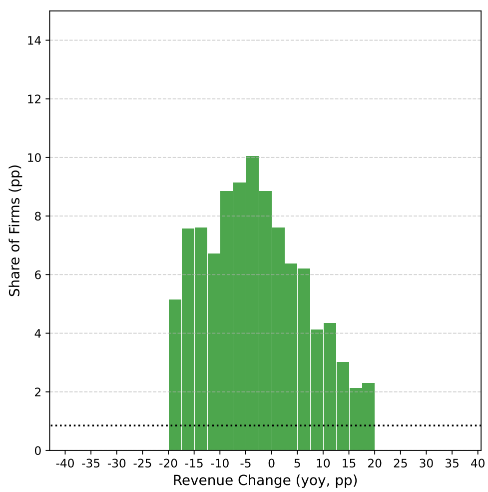
Notes: Panel (b) and (c) shows how optimal *capacity*, c, and *fixed labor*, γc, change as a function of firm-specific human capital γ. The constraint considered is $P[CF < 0|Y = (1 - a)] < \alpha$. The model is numerically solved for the following set of parameters: $\mu = 10, \sigma = 2, b = 2, a = 0.1, p = 0.1, w = 0.4, \alpha = 0.01, k = 0.01, q_{min} = 0.02$. The remaining panels illustrate the model solution (black dot) for increasing levels of γ from panel (a) to (c). Panels (a), (b) and (c) correspond to cases a), b) and c) in Proposition 1, respectively. On the x-axes the *capacity*, c, and on the y-axis the amplitude of the hedged exchange rate, $q = (a - h)$, is depicted. In each panel, the blue line corresponds to points on which the Lagrange optimality is satisfied, the yellow line to unconstrained optimal capacity choices for given levels of q, and the red line to points on which the constraint binds.

Figure C.4: Further Sample Characteristics

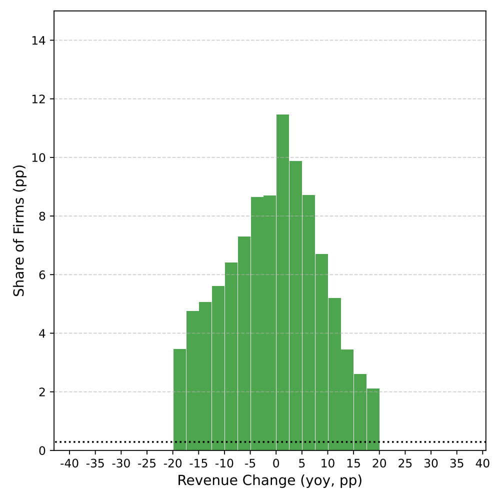
(a) Industry Composition



(b) Δ Revenue Full Sample



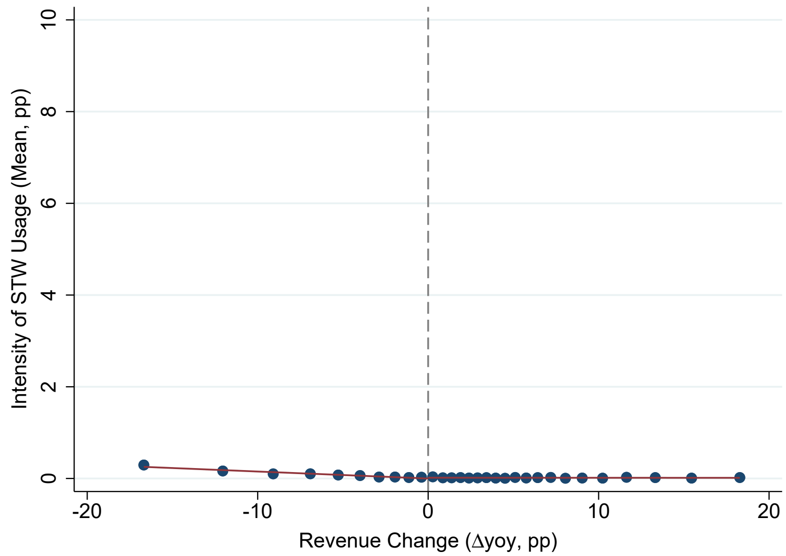
(c) Δ Revenue Sample with FX Data



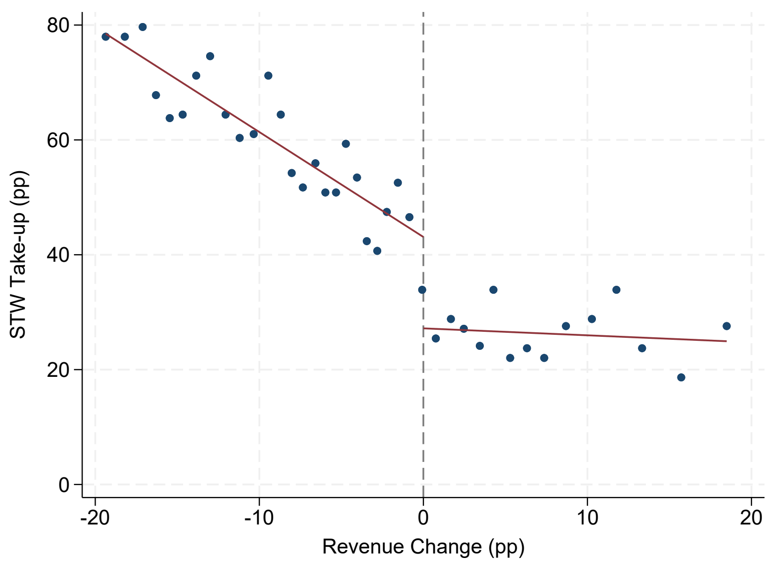
Notes: Panel (a) figure shows the industry compostion in the full sample vs. the sample of firms with FX data (cf. Panel (a) vs. Panel (b) of Table 1). Panels (b) and (c) shows the year-on-year revenue change in 2020 (in pp) for the full sample vs. the sample of firms with FX data.

Figure C.5: Measure: Placebo and Binary Outcome

(a) Placebo 2012-2019: STW Usage Intensity by Firm-Level Revenue Change

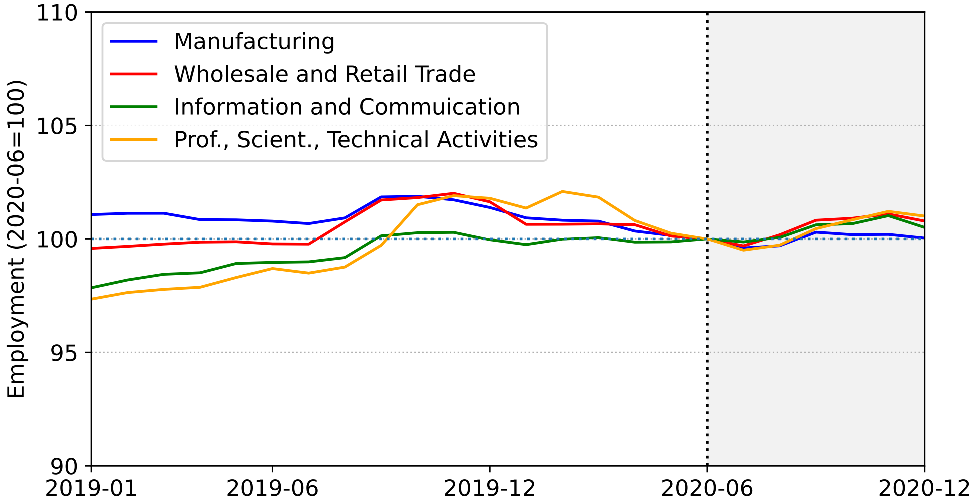


(b) STW Usage 2020 (Binary)



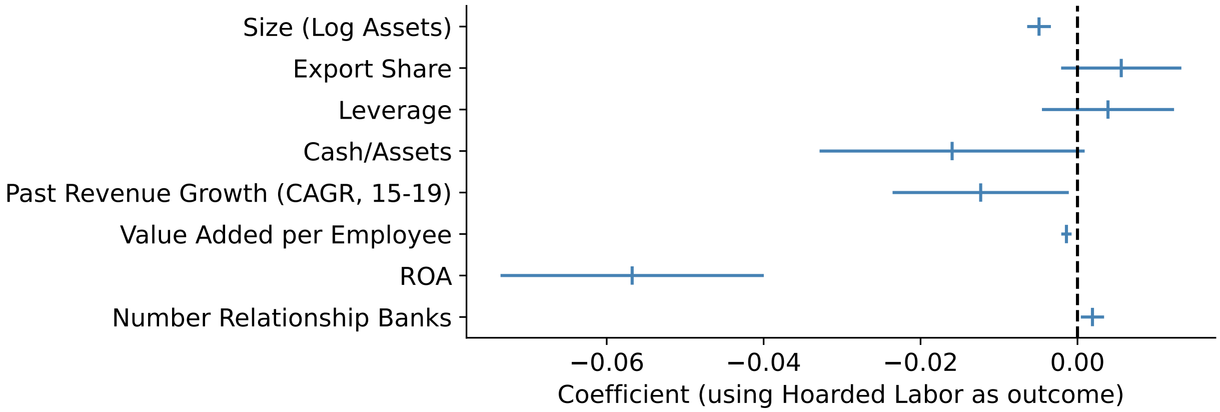
Notes: Panel (a) shows a replication of Figure 4 outside an eased-access episode. The sample consists of pooled firm-year observations for the years 2012-2019. The annual *Intensity of STW Usage* in a given year is defined analogously to before (cf. section 3.3) based on all months per year. On the y-axis is the annual year-on-year change in revenue (in pp).

Figure C.6: Monthly Industry-Wide Employment



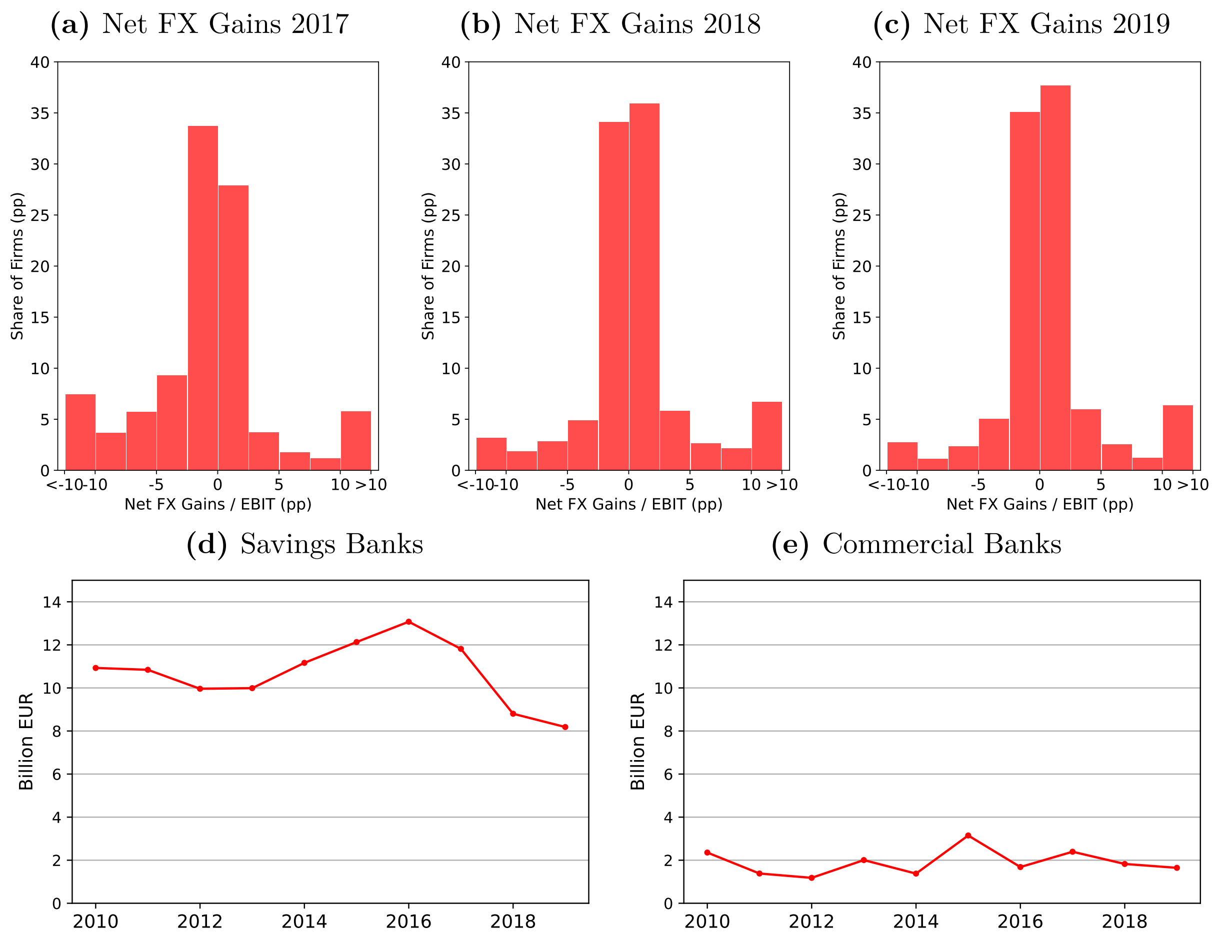
Notes: The figure shows monthly employment in the four largest industries. The results are based on the full sample of firms (see panel (a) of Table 1). The shaded area indicates months upon which the measure for hoarded labor is based (see section 3.3 for details). Employment in June 2020 is normalized to 100.

Figure C.7: Who Hoards?



Notes: The figure shows the estimated OLS coefficients and 95% confidence intervals of a regression of *Hoarded Labor* on firm characteristics. The results are based on the full sample of firms (see panel (a) of Table 1). Firm characteristics are as of 2019 (or available information in Dafne as of May 2022 for *Export Share*). Workforce characteristics are as of 2019. For details on the shortage share-based measure and the vocational training-based measure see section 7.1.

Figure C.8: Relevance of FX Risk



Notes: Panels (a) - (c) show the distribution of net FX gains scaled by EBIT (in pp) in the years 2017 - 2019. Attention is restricted per year to firms with positive EBIT. The rightmost (leftmost) bins in each panel correspond to firms with net FX gains to EBIT above 10% (below -10%), grouped due to data protection. The results are based on firms with FX data (see panel (b) of Table 1). Panels (d) and (e) show outstanding amounts of FX derivatives aggregated per banking group: savings banks (*Sparkassen*) in panel (a) and commercial banks (*Volksbanken*) in panel (b). For details on the construction of the dataset see Appendix B6.

D Supplementary Tables

Table D.1: Robustness: Comovement of Changes in Profitability with Industry-Wide Demand by Labor Hoarding

(a) Industry-Wide Order Changes

	Dep. Variable:					
	ROA (Δ yoy)			CF (Δ yoy)		
	(1)	(2)	(3)	(4)	(5)	(6)
Labor Hoarding	-0.044			-0.132***		
	(0.05)			(0.04)		
Labor Hoarding × Δ Industry-Level Orders	0.298	0.565**	0.830**	0.152	0.259	0.304
	(0.25)	(0.25)	(0.34)	(0.16)	(0.17)	(0.23)
N Firms	1437	1437	1437	1436	1436	1436
R^2	0.041	0.160	0.306	0.045	0.178	0.307
Adj. R^2	0.001	-0.003	-0.010	0.005	0.018	-0.010
N Observations	11,734	11,718	10,502	11,702	11,686	10,474

(b) Summary Statistics

	Mean	SD	p5	p50	p95	N
All Sectors						
ROA (Δ yoy)	-0.065	2.465	-2.289	-0.083	2.379	38,250
Cash Flow (Δ yoy)	0.000	0.014	-0.014	0.000	0.015	38,144
Δ Industry-Level Demand	0.078	0.086	-0.096	0.103	0.178	38,250
Upturns						29,647
Robustness: Manufacturing						
ROA (Δ yoy)	-0.119	2.520	-2.486	-0.097	2.281	10,502
Cash Flow (Δ yoy)	0.000	0.014	-0.015	0.000	0.015	10,473
Δ Industry-Level Orders	0.031	0.150	-0.154	0.000	0.244	10,502
Upturns						5,185

Notes: Panel (a) reports the results of regression (R1) in a firm-year panel from 2010-2020. The results are based on the full sample of firms (see panel (a) of Table 1). Attention is restricted to manufacturing firms due to data availability of orders. *Labor Hoarding* is a binary firm-level variable that takes the value of 1 if the firm uses STW in the eased-access episode in 2020 (June-December), for details see section 3.3. Robust standard errors, clustered at the industry level, are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel (b) provides summary statistics for the panel analyses in Table 2 and Panel (a). Δ *Industry-Level Demand* is the year-on-year change in the ifo Business Climate index (6m-ahead expectations, provided by the ifo Institut) per sector as of March each year. Δ *Industry-Level Orders* is the relative year-on-year change in industry-level orders as of March each year. It is a value index, normalized to 100 in 2015 (raw series), from the Federal Statistical Office of Germany (tables 42151-0002). *Upturns* is a count of observations with a positive change in either measure.

Table D.2: Heterogeneity along the Model Comparative Statics

	Dep. Variable: FX-Induced CF Volatility							
Heterogeneity Dimension:	Low Labor Share		Low Order Volatility		Low Leverage		More Than 3 Banks	
	sd	max	sd	max	sd	max	sd	max
Hoarded Labor	-1.146***	-1.803***	-0.748*	-0.676	-0.607*	-1.399***	-0.961***	-1.817***
	(0.32)	(0.47)	(0.42)	(0.61)	(0.31)	(0.51)	(0.30)	(0.47)
Heterogeneity Dimension × Hoarded Labor	0.971**	1.185*	0.896*	0.466	-0.252	0.306	0.886**	2.217***
	(0.43)	(0.64)	(0.53)	(0.83)	(0.42)	(0.64)	(0.45)	(0.64)
Heterogeneity Dimension	-0.069*	-0.110	-0.125**	-0.078	-0.004	-0.078	-0.106***	-0.247***
	(0.04)	(0.07)	(0.06)	(0.09)	(0.04)	(0.06)	(0.04)	(0.06)
Log Assets	0.070***	0.102***	0.050*	0.063	0.070***	0.102***	0.077***	0.121***
	(0.02)	(0.03)	(0.03)	(0.04)	(0.02)	(0.03)	(0.02)	(0.03)
Export Share	0.477***	0.736***	0.352***	0.498***	0.479***	0.750***	0.476***	0.730***
	(0.08)	(0.13)	(0.11)	(0.18)	(0.08)	(0.13)	(0.08)	(0.13)
Revenue Change 19-20	-0.009	-0.125	0.466	0.605	-0.005	-0.112	0.007	-0.039
	(0.21)	(0.31)	(0.29)	(0.43)	(0.21)	(0.31)	(0.22)	(0.32)
Value Added per Employee	0.014	-0.003	2.299**	3.471**	0.014	-0.004	0.012	-0.008
	(0.01)	(0.01)	(1.02)	(1.70)	(0.01)	(0.01)	(0.01)	(0.01)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.120	0.101	0.163	0.117	0.117	0.100	0.121	0.105
Adj. R^2	0.080	0.061	0.137	0.090	0.078	0.060	0.081	0.064
N Firms	1,640	1,640	738	738	1,640	1,640	1,559	1,559

Notes: The table reports the estimated OLS coefficients from specification (R2) allowing for heterogeneity of the effect in four different dimensions. In columns 1 and 2, a granular (3-digit) industry has a *Low Labor Share* if its average labor share (wagebill to value added) is below median. In columns 3 and 4, a granular (3-digit) industry has a *Low Order Volatility* if the standard deviation of monthly industry-level orders between 2010 and 2020 is below median (data only available for the manufacturing sector). In columns 5 and 6, a firm has a low leverage if its equity-to-asset ratio is above p66. In columns 7 and 8, *More Than 3 Banks* is an binary variable equal to 1 if the firms has more than three banking relationships. Two versions of the variable *FX-Induced CF Volatility* are considered: standard deviation of net FX gains to revenue (*sd*) and maximum of net FX losses to revenue (*max*) (see section 6.2 for details). For details on the construction of *Hoarded Labor* see section 3.3. Control variables are as of 2019 (or available information in Dafne as of May 2022 for *Export Share*). Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.3: Robustness OLS

	Dep Variable: FX-Induced CF Volatility					
	OLS		OLS		OLS	
	sd	max	sd	max	sd	max
Hoarded Labor	-0.450**	-0.764**	-0.707***	-1.263***	-0.518**	-0.891**
	(0.20)	(0.37)	(0.26)	(0.39)	(0.21)	(0.39)
Log Assets	0.065***	0.099***	0.070***	0.102***	0.064***	0.097***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Export Share	0.456***	0.692***	0.478***	0.742***	0.459***	0.696***
	(0.06)	(0.10)	(0.08)	(0.13)	(0.06)	(0.10)
Revenue Change 19-20	-0.039	-0.037	-0.004	-0.118	-0.047	-0.052
	(0.16)	(0.26)	(0.21)	(0.32)	(0.16)	(0.26)
Value Added per Employee			0.014	-0.004		
			(0.01)	(0.01)		
ROA (pp)					-0.002*	-0.003*
					(0.00)	(0.00)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.112	0.092	0.117	0.099	0.113	0.094
Adj. R^2	0.082	0.061	0.079	0.060	0.082	0.062
N Firms	2,319	2,319	1,640	1,640	2,319	2,319

Notes: The table reports estimated OLS coefficients from specification (R2) with varying controls. For details on the construction of *Hoarded Labor* see section 3.3. Control variables are as of 2019 (or available information in Dafne as of May 2022 for *Export Share*). Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.4: Summary Statistics for Firms with Above/Below Median FSHC

(a) Shortage Occupation-Based

	Below Median Short Occup-Based					Above Median Short Occup-Based					t-test Means
	Mean	p10	p50	p90	N	Mean	p10	p50	p90	N	
Core Financial Information (2019)											
Assets (mil EUR)	263.92	13.81	44.99	250.32	1176	347.59	14.49	47.04	276.55	1176	0.62
Revenue (mil EUR)	216.27	24.20	77.10	350.46	1176	257.23	21.13	68.10	320.14	1176	0.58
Employees	311.74	37.00	168.50	583.00	1176	589.73	90.00	279.50	907.00	1176	0.01
Leverage (pp)	60.36	23.25	59.55	94.10	1176	58.18	23.74	58.19	89.63	1176	0.09
Cash/Assets (pp)	9.56	0.03	4.00	27.36	1176	9.50	0.03	4.31	27.34	1176	0.92
ROA (pp)	7.80	-4.10	6.23	22.68	1176	7.09	-5.25	6.04	20.65	1176	0.21
Value Added per Employee (mil EUR)	0.17	0.05	0.10	0.26	823	0.16	0.05	0.09	0.15	838	0.91
Firm-Level Employment Characteristics (2019)											
Avrg Age (years)	42.89	38.08	43.07	47.40	1176	42.76	38.68	43.03	46.67	1176	0.37
Avrg Wage (EUR, daily, FT)	133.45	92.24	131.35	177.55	1176	132.19	97.42	131.92	167.38	1176	0.31
Avrg Tenure (years)	9.87	4.68	9.45	14.98	1176	11.16	5.75	10.75	16.93	1176	0.00
Further											
Export Share	0.41	0.05	0.40	0.80	1176	0.47	0.08	0.49	0.82	1176	0.00
1(Exports to Outside Europe)	0.78	0.00	1.00	1.00	548	0.86	0.00	1.00	1.00	644	0.00
1(Financial Hedging 2019)	0.28	0.00	0.00	1.00	1176	0.25	0.00	0.00	1.00	1176	0.12
Number of Banks	2.52	1.00	2.00	4.00	1107	2.72	1.00	3.00	5.00	1117	0.00
1(Relationship Bank: Local)	0.46	0.00	0.00	1.00	1107	0.57	0.00	1.00	1.00	1117	0.00
1(Relationship Bank: Grossbank)	0.84	0.00	1.00	1.00	1107	0.86	0.00	1.00	1.00	1117	0.18

(b) Vocational Training-Based

	Below Median Voc Training-Based					Above Median Voc Training-Based					t-test Means
	Mean	p10	p50	p90	N	Mean	p10	p50	p90	N	
Core Financial Information (2019)											
Assets (mil EUR)	441.90	13.31	48.20	314.40	1176	169.61	15.15	43.87	226.12	1176	0.11
Revenue (mil EUR)	296.33	20.84	73.41	371.77	1176	177.17	25.13	72.33	291.98	1176	0.11
Employees	483.44	42.00	188.00	692.00	1176	418.02	70.00	253.00	771.00	1176	0.53
Leverage (pp)	61.54	24.79	61.26	93.37	1176	57.00	21.96	57.22	89.72	1176	0.00
Cash/Assets (pp)	11.03	0.04	5.10	31.17	1176	8.04	0.02	3.28	22.80	1176	0.00
ROA (pp)	7.98	-4.51	6.53	23.35	1176	6.91	-4.57	5.77	20.03	1176	0.06
Value Added per Employee (mil EUR)	0.24	0.06	0.11	0.24	834	0.10	0.05	0.08	0.15	827	0.05
Firm-Level Employment Characteristics (2019)											
Avrg Age (years)	42.67	37.50	42.91	47.39	1176	42.98	39.14	43.19	46.78	1176	0.03
Avrg Wage (EUR, daily, FT)	144.00	104.32	144.07	181.87	1176	121.64	88.85	121.07	153.76	1176	0.00
Avrg Tenure (years)	9.24	4.51	8.86	14.33	1176	11.79	6.50	11.39	17.61	1176	0.00
Further											
Export Share	0.44	0.06	0.43	0.85	1176	0.45	0.08	0.45	0.80	1176	0.39
1(Exports to Outside Europe)	0.84	0.00	1.00	1.00	553	0.81	0.00	1.00	1.00	639	0.26
1(Financial Hedging 2019)	0.27	0.00	0.00	1.00	1176	0.26	0.00	0.00	1.00	1176	0.48
Number of Banks	2.44	1.00	2.00	4.00	1114	2.80	1.00	3.00	5.00	1110	0.00
1(Relationship Bank: Local)	0.45	0.00	0.00	1.00	1114	0.58	0.00	1.00	1.00	1110	0.00
1(Relationship Bank: Grossbank)	0.84	0.00	1.00	1.00	1114	0.87	0.00	1.00	1.00	1110	0.11

Notes: The table reports firm-level summary statistics separately for firms with an above- or below-median level of FSHC, as captured by the shortage occupation-based measure in Panel (a) or the vocational training-based measure in Panel (b).

Table D.5: Occupational Composition across Time

	Occupational Shares of 2019 Top 3 Occupations					
	(1)	(2)	(3)	(4)	(5)	(6)
Log Assets	0.045***	-0.013***	0.037**	0.017**	-0.012***	-0.004
	(0.02)	(0.00)	(0.02)	(0.01)	(0.00)	(0.01)
L.Export Share				-0.021	-0.104***	0.006
				(0.01)	(0.01)	(0.02)
Firm FEs	Yes	No	Yes	Yes	No	Yes
Year FEs	No	Yes	Yes	No	Yes	Yes
R Squared	0.701	0.009	0.702	0.899	0.046	0.912
R Squared Adj.	0.624	0.009	0.625	0.858	0.045	0.861
N Observations	13,438	13,438	13,438	4,633	3,124	2,863
N Firms	2,741	2,741	2,741	1,342	1,342	1,041

Notes: The table shows the estimated coefficients from a panel regression of the share of (firm-level) top-3 occupations (as of 2019) on size in columns 1-3 and size and lagged export share in columns 4-6. The panel is from 2015 until 2019. Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.6: Robustness for Shortage Occupation-Based Instrument

(a) Including Further Controls

	Dep. Variable: FX-Induced CF Volatility					
	2SLS		2SLS		2SLS	
	sd	max	sd	max	sd	max
Hoarded Labor	-7.192***	-13.069***	-6.984**	-13.036**	-7.891***	-14.348***
	(2.654)	(4.750)	(3.132)	(5.346)	(2.918)	(5.220)
Log Assets	0.030	0.036	0.039	0.043	0.024	0.024
	(0.020)	(0.033)	(0.026)	(0.041)	(0.021)	(0.036)
Export Share	0.512***	0.793***	0.564***	0.903***	0.524***	0.815***
	(0.067)	(0.113)	(0.095)	(0.151)	(0.069)	(0.117)
Revenue Change 19-20	-1.308**	-2.353**	-1.315*	-2.577**	-1.420**	-2.559**
	(0.536)	(0.940)	(0.704)	(1.194)	(0.577)	(1.014)
Value Added per Employee			0.008	-0.015**		
			(0.011)	(0.008)		
ROA					-0.006***	-0.011***
					(0.002)	(0.003)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Instrument 1st Stage	.028	.028	.029	.029	.026	.026
Partial R Squared 1st Stage	.009	.009	.022	.022	.008	.008
Kleibergen-Paap F-statistic	23.036	23.036	18.036	18.036	20.395	20.395
N Firms	2,319	2,319	1,640	1,640	2,319	2,319

(b) Subset of Firms with Confirmed Export Destinations Outside the Euro Area

	Dep. Variable: FX-Induced CF Volatility					
	OLS		2SLS		Reduced Form	
	sd	max	sd	max	sd	max
Hoarded Labor	-0.493*	-0.619	-8.485**	-13.533**		
	(0.283)	(0.483)	(3.587)	(6.301)		
Log Assets	0.055**	0.090***	0.019	0.032	0.056**	0.092***
	(0.024)	(0.031)	(0.032)	(0.049)	(0.023)	(0.030)
Export Share	0.539***	0.745***	0.625***	0.885***	0.537***	0.745***
	(0.097)	(0.156)	(0.123)	(0.199)	(0.096)	(0.154)
Revenue Change 19-20	0.083	0.567	-1.529**	-2.037	0.141	0.627*
	(0.217)	(0.385)	(0.760)	(1.379)	(0.200)	(0.369)
FSHC (Shortage Occupation-Based)					-0.317***	-0.506***
					(0.099)	(0.186)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Instrument 1st Stage			.037	.037		
Partial R Squared 1st Stage			.011	.011		
Kleibergen-Paap F-statistic			11.459	11.459		
N Firms	957	957	957	957	957	957

Notes: The table reports robustness checks for specifications (R3). In Panel (a) we further control for value added per employee and return on assets. Panel (b) restricts attention to firms with export-destination information that export to outside of Europe. Two versions of the variable *FX-Induced CF Volatility* are considered: standard deviation of net FX gains to revenue (*sd*) and maximum of net FX losses to revenue (*max*) (see section 6.2 for details). Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.7: Using Both Instruments

	Dep. Variable: FX-Induced CF Volatility					
	2SLS		2SLS		2SLS	
	sd	max	sd	max	sd	max
Hoarded Labor	-10.280***	-17.811***	-11.391***	-20.994***	-11.219***	-19.450***
	(2.975)	(5.280)	(3.548)	(6.194)	(3.289)	(5.810)
Log Assets	0.015	0.012	0.017	0.004	0.006	-0.004
	(0.022)	(0.036)	(0.030)	(0.046)	(0.024)	(0.040)
Export Share	0.537***	0.832***	0.624***	1.011***	0.553***	0.860***
	(0.074)	(0.126)	(0.108)	(0.180)	(0.077)	(0.130)
Revenue Change 19-20	-1.889***	-3.246***	-2.236***	-4.241***	-2.040***	-3.509***
	(0.584)	(1.032)	(0.765)	(1.344)	(0.633)	(1.116)
Value Added per Employee			0.004	-0.022**		
			(0.011)	(0.009)		
ROA					-0.008***	-0.014***
					(0.002)	(0.004)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Instrument 1st Stage						
Kleibergen-Paap F-statistic	13.559	13.559	11.925	11.925	12.025	12.025
Overidentification Test χ^2 p-value	0.031	0.033	0.046	0.022	0.035	0.039
N Firms	2,319	2,319	1,640	1,640	2,319	2,319

Notes: The table reports the estimated coefficients from a specification analogous to (R3) now instrumenting *Hoarded Labor* with the shortage occupation-based and vocational training-based instruments. Two versions of the variable *FX-Induced CF Volatility* are considered: standard deviation of net FX gains to revenue (*sd*) and maximum of net FX losses to revenue (*max*) (see section 6.2 for details). For details on the construction of *Hoarded Labor* see section 3.3. Control variables are as of 2019 (or available information in Dafne as of May 2022 for *Export Share*). Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.8: Robustness with Hoarded Labor Based on the 2009 Eased-Access Episode

	Dep. Variable: FX-Induced CF Volatility					
	OLS		2SLS		Reduced Form	
	sd	max	sd	max	sd	max
Hoarded Labor (2009)	-0.572**	-0.763*	-23.414*	-40.997*		
	(0.24)	(0.40)	(13.30)	(22.87)		
Log Assets 2008	0.056***	0.099***	-0.013	-0.020	0.054***	0.098***
	(0.02)	(0.03)	(0.04)	(0.08)	(0.02)	(0.03)
Export Share	0.462***	0.779***	0.749***	1.276***	0.435***	0.725***
	(0.07)	(0.12)	(0.18)	(0.31)	(0.07)	(0.12)
Revenue Change 08-09	0.087	0.216**	-1.569*	-2.701*	0.105	0.233**
	(0.08)	(0.11)	(0.94)	(1.62)	(0.07)	(0.11)
Share Vocational Training					-0.366***	-0.633***
					(0.12)	(0.19)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Instrument 1st Stage			.016	.016		
Partial R^2 1st Stage			.006	.006		
Kleibergen-Paap F-statistic			3.993	3.993		
Anderson-Rubin χ^2 p-value			0.003	0.001		
N Firms	1,558	1,558	1,554	1,554	1,560	1,560

Notes: The table reports a robustness check for specifications (R3). *Hoarded Labor* is constructed based on STW usage during the eased-access episode in 2009 (see section 3.3 for details). Control variables as well as *Vocational Share* are as of 2008. Two versions of the variable *FX-Induced CF Volatility* are considered: standard deviation of net FX gains to revenue (*sd*) and maximum of net FX losses to revenue (*max*) (see section 6.2 for details). Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.9: Stylized Facts on FX-Derivatives Usage

(a) Summary Statistics of Users vs. Non-users

	Non-User 2019					Derivatives User 2019					t-test Means
	Mean	p10	p50	p90	N	Mean	p10	p50	p90	N	
Core Financial Information (2019)											
Assets (mil EUR)	111.25	12.38	40.99	171.82	1729	845.55	20.76	80.06	535.91	623	0.00
Revenue (mil EUR)	128.73	19.85	63.53	227.49	1729	536.53	35.02	114.71	772.64	623	0.00
Employees	307.04	55.00	203.00	588.00	1729	849.52	52.00	283.00	1286.00	623	0.00
Equity/Assets (pp)	40.56	6.63	41.80	77.10	1729	41.19	10.46	39.73	75.21	623	0.67
Cash/Assets (pp)	9.86	0.03	4.52	28.11	1729	8.62	0.04	3.43	24.31	623	0.04
ROA (pp)	7.82	-4.73	6.44	22.68	1729	6.42	-3.97	5.43	19.04	623	0.03
Value Added per Employee (mil EUR)	0.16	0.05	0.09	0.19	1214	0.19	0.06	0.10	0.21	447	0.72
Information on Exports and FX-Volatility											
Export Share	0.42	0.06	0.40	0.80	1729	0.51	0.11	0.55	0.85	623	0.00
FX-Induced CF Volatility (sd)	0.28	0.00	0.09	0.72	1729	0.44	0.02	0.21	1.03	623	0.00
FX-Induced CF Volatility (max)	0.44	0.00	0.10	1.16	1729	0.64	0.01	0.24	1.48	623	0.00
1(Export Outside Europe)	0.80	0.00	1.00	1.00	877	0.89	0.00	1.00	1.00	315	0.00

(b) Weakening Link between Export Share and FX-induced CF volatility

	Dep. Variable: FX-Induced CF Volatility (sd)			
	Baseline		Exports Outside EA	
	(1)	(2)	(3)	(4)
Export Share	0.489***	0.477***	0.652***	0.542***
	(0.06)	(0.07)	(0.10)	(0.10)
Export Share × Derivatives Usage	-0.210*	-0.091	-0.429**	-0.225
	(0.12)	(0.18)	(0.19)	(0.24)
Derivatives Usage	0.203***	0.160**	0.317***	0.200
	(0.07)	(0.08)	(0.11)	(0.12)
Log Assets	0.059***	0.022	0.048**	0.031
	(0.02)	(0.01)	(0.02)	(0.02)
Import Share		0.271***		0.431***
		(0.07)		(0.09)
Industry x Region FEs	Yes	Yes	Yes	Yes
R^2	0.117	0.138	0.153	0.170
Adj. R^2	0.087	0.093	0.108	0.108
N Firms	2,319	936	957	555

(c) Non-Link between Ixport Share and FX-induced CF volatility

	Dep. Variable: FX-Induced CF Volatility (sd)			
	Baseline		Exports Outside EA	
	(1)	(2)	(3)	(4)
Import Share	0.254***	0.224***	0.418***	0.366***
	(0.08)	(0.07)	(0.11)	(0.10)
Import Share × Derivatives Usage	0.141	0.185	0.173	0.252
	(0.14)	(0.14)	(0.18)	(0.17)
Derivatives Usage	0.088	0.042	0.040	-0.012
	(0.06)	(0.06)	(0.08)	(0.07)
Log Assets	0.038**	0.023*	0.050***	0.032*
	(0.01)	(0.01)	(0.02)	(0.02)
Export Share		0.457***		0.482***
		(0.08)		(0.12)
Industry x Region FEs	Yes	Yes	Yes	Yes
R^2	0.089	0.140	0.123	0.172
Adj. R^2	0.042	0.095	0.059	0.110
N Firms	936	936	555	555

Notes: Panel (a) shows summary statistics separately for derivatives users (as of 2019, RHS) and non-users (LHS). *Export Share* (*Import Share*) is the information availabe from Creditreform (as of May 2022). The bottom panels report estimated OLS coefficients from a regression of *FX-Induced CF Volatility* (*sd*) on the export share in Panel (a) and import share in Panel (b), allowing for heterogeneity between derivatives users and non-users. *Derivatives Usage* is equal to 1 if the firm uses FX derivatives in 2019. Control variables are as of 2019 (or available information in Dafne as of May 2022 for *Export Share*). Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.