Do Firms Hedge Human Capital?

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November 7, 2024

Abstract

I study how firms' labor hoarding, driven by their reliance on firm-specific human capital, affects their hedging of other business risks. Leveraging German administrative data on short-time work, combined with matched employer-employee data and firm financial information, I develop a firm-level measure of hoarded labor. I formalize the hypothesized risk trade-off in a stylized model featuring demand uncertainty and uncertainty around an unrelated price risk that can be hedged at a cost. Empirically, labor-hoarding firms exhibit larger comovements of their cash flows (CF) with demand fluctuations, illustrating the upside potential of hoarded labor functioning as a capacity increase. However, labor hoarding is not linked to higher overall CF volatility; instead, it is linked to reduced foreign-exchange (FX) risk as one specific price risk. FX risk can substantially contribute to CF volatility, especially for smaller, globally exporting firms that are sensitive to the driving forces of labor hoarding suggested by the model: idiosyncratic demand risk and reliance on firm-specific human capital. I instrument hoarded labor with proxies for firm-specific human capital and find that firms hedge their FX risk more in response to greater labor hoarding. These findings offer a new perspective on firms' willingness to assume risk in the context of labor market rigidities and institutions.

JEL classifications: J01, J24, G00, G32

Keywords: labor hoarding, human capital, risk management, FX risk

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*University of Bonn. Email: christina-brinkmann@uni-bonn.de. I am grateful to my advisor, Farzad Saidi, and to my other committee members, Xavier Giroud, Simon Jäger, and Moritz Kuhn, for their guidance and continuous support. I thank Stefanie Wolter from the Research Institute of the Federal Employment Agency (IAB) for her constant support in making this project possible. I also thank Ramin Baghai (discussant), Edoardo Acabbi, Kent Daniel, Olivier Darmouni, Martin Hellwig, Christian Kubitza, Yiming Ma, Adrien Matray, Jesse Schreger, Martin Schmalz, Suresh Sundaresan, Jing Zeng, and fellow BGSE students and post-docs, as well as seminar participants at the EFA Doctoral Tutorial 2024, Bonn Finance Seminar, Bonn-Frankfurt-Mannheim PhD Conference 2024, ECONtribute's YEP Seminar, and PhD Seminar at Columbia Business School for helpful comments and suggestions. I thank Tobias Günther for valuable research assistance. I gratefully acknowledge funding by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy (EXC 2126/1 – 390838866) and through CRC TR 224 (Project C03). This work was supported by a fellowship of the German Academic Exchange Service (DAAD).

1 Introduction

Labor is a partially fixed input to production (Oi, 1962), due to factors such as the time needed to train employees for certain tasks or to build firm-specific knowledge. Therefore, employment decisions, made under uncertainty around future demand, are inherently risky. Higher employment levels reduce the likelihood of personnel shortages limiting production, whereas during periods of low demand, firms face a larger wage bill and have more temporarily idle labor (hoarded labor). This trade-off is reflected in the two most frequently stated reasons for production being below full production capability: insufficient orders and insufficient supply of labor.[1] In particular, although labor hoarding – driven by reliance on firm-specific human capital – may be profitable over a longer horizon, it increases cash-flow (CF) volatility. This raises the question of how firms' labor hoarding affects their broader risk management.

Measuring and understanding firms' labor-hoarding behavior has been a fundamental challenge since the 1960s (Okun, 1963; Biddle, 2014). Existing work has relied on survey evidence (Fay and Medoff, 1985) or indirect ways of measuring labor hoarding (Fair, 1969; Clark, 1973; Rotemberg and Summers, 1990), leaving broad empirical measurement at the firm level elusive. At the same time, the corporate finance literature has highlighted the role of fixed labor expenses for operating leverage, that is, the sensitivity of operating income to sales fluctuations, inducing firms to make asset-side (Ghaly, Anh Dang, and Stathopoulos, 2017) and liability-side (Simintzi, Vig, and Volpin, 2015) adjustments to their balance sheets. By using fixed labor expenses, this approach focuses on downside risk, whereas the mechanism in a labor-hoarding channel of risk management also incorporates upside potential of labor hoarding: it facilitates higher production levels, which, coupled with room for price increases when the industry operates near capacity (Boehm and Pandalai-Nayar, 2022), may render labor hoarding particularly profitable during these times.

In this paper, I introduce a novel way to measure labor hoarding and show that firms with more hoarded labor due to stronger reliance on firm-specific human capital offset the resulting increase in CF sensitivity to demand fluctuations by reducing other business risk. To that end, I leverage novel data on short-time work (STW) in Germany, combined with matched employer-employee data and firm financial information, including hand-collected hedging data. I study firms' management of foreign-exchange (FX) risk – a natural candidate for a specific business risk to focus on. First, it is a price risk unrelated to other risks in the short run. Second, it is empirically relevant for firms sensitive to driving forces behind labor hoarding: idiosyncratic demand risk and reliance on firm-specific human capital. This is often the case for smaller firms in the tradable sector, typical in export-oriented European

1 See Figure 1, based on the Quarterly Survey of Plant Capacity Utilization of the US Census Bureau.

economies, because such firms are often technologically highly specialized and operate in volatile global niche markets while facing FX risk through the USD dominance in global trade (Barbiero, 2021).[2]

I begin by presenting a model that serves two purposes: it provides a theoretical framework to formalize a labor-hoarding channel of risk management, and it generates predictions, which I empirically test in the remainder of the paper. The model has three key components. First, it features demand uncertainty and uncertainty about an unrelated price risk that can be hedged ex ante at a cost. Second, it explicitly includes *hoarded labor*, defined as expected unused fixed labor, facilitating a close mapping to the empirical setup later. Third, it introduces *firm-specific human capital* as a dimension of firm-level heterogeneity driving labor-hoarding choices, which informs my identification strategy in the empirical analysis.

At the core of the stylized two-period model is a risk trade-off, influenced by the level of firm-specific human capital. Firms rely on workers with specialized skills who must be hired before demand is known (*fixed labor*). The level of fixed labor sets a capacity limit for future production. More capacity increases expected CF but also raises the default probability. A risk-averse firm that seeks to maintain a default probability below some threshold thus increases its hedging of the unrelated price risk to offset the higher default probability associated with more fixed labor. Firms differ in their reliance on fixed labor, reflecting their level of firm-specific human capital. Then, the model predicts that, first, in the cross section of firms, firms that hoard more labor, due to greater firm-specific human capital, hedge more, thereby reducing their exposure to unhedged FX risk. Second, firms with more firm-specific human capital are expected to hoard more labor.

To empirically test a labor-hoarding channel of risk management, I construct a measure for hoarded labor by drawing on firms' STW usage during episodes of eased access. STW is a subsidy that enables eligible firms to flexibly reduce work hours while employees are compensated for a large part of the associated wage gap (Giupponi, Landais, and Lapeyre, 2022). Receipt of the subsidy requires detailed documentation on the reduction in hours per employee. Typically, access to STW is highly restricted, but these restrictions have been relaxed during certain episodes. During these eased-access episodes, a broad range of firms – including those with normal operations – became eligible, with STW incentivizing the disclosure of temporarily unused labor. I define hoarded labor empirically as firms' average monthly STW usage intensity during an eased-access episode in the second half of 2020.

Although the empirical measure is based on ex-post levels of underutilized labor whereas

2 Around 20% of German exports and imports are USD denominated (Boz, Casas, Georgiadis, Gopinath, Le Mezo, Mehl, and Nguyen, 2022).

labor hoarding is an ex-ante concept, the measure remains suitable for studying labor hoarding, especially in the context of firms' risk management. An ideal empirical measure of hoarded labor would capture firms' ex-ante choices of expected idle employee hours per month, associated with the chosen level of employment and, thus, production capacity. STW reflects the ex-post realized hours of employee downtime, even when averaged over several months, as done here. This difference does not undermine the measure's validity in a correlation with FX risk, provided the difference between firms' ex-ante chosen labor hoarding and the ex-post measurement does not systematically vary with firms' FX risk conditional on year-on-year revenue development and industry-by-region fixed effects. The same holds in the instrumental variable (IV) design as long as the difference is additionally independent of the instrument.

I address concerns that an empirical measure based on 2020 reflects primarily the effect of the COVID-19 shock by restricting the sample to firms less affected by the pandemic and by providing evidence strongly suggesting STW usage in 2020 reveals baseline underutilization levels beyond the COVID-19 shock. Specifically, I restrict the sample in three ways: by excluding data from the lockdown months until May when constructing the measure; by excluding firms with year-on-year revenue changes below -20% or above 20%; and by focusing naturally (due to FX data availability) on sectors such as the tradable-goods sector, which are less reliant on personal interactions. I then present evidence indicating that STW usage during the eased-access episode in 2020 reflects more than just the COVID-19 shock. To that end, I show STW was widely used in 2020, even by firms without substantial revenue declines or with positive revenue growth, and during months with industry-wide production similar to 2019. An additional comparison of firms that used STW with those that did not shows no significant differences in size, age, past revenue growth, or export share, further corroborating the interpretation.

Focusing on the role of demand uncertainty for labor hoarding, I demonstrate that labor hoarding allows firms to profit more from economic upturns. Specifically, I use a firm-year panel between 2010 and 2020 and identify labor-hoarding firms based on the previously defined measure. As expected, I find the comovement of changes in profitability with industry-wide upturns and downturns is stronger for labor-hoarding firms than for their non-labor-hoarding counterparts.

I next examine the relationship between labor hoarding and firms' CF volatility and find firms with higher levels of labor hoarding have lower FX-induced CF volatility, although their overall CF volatility remains comparable to other firms. Specifically, I construct measures of FX risk net of hedging (*FX-induced CF volatility*) from accounting information on FX transaction income following Adams and Verdelhan (2022). The observed negative correlation between hoarded labor and FX-induced CF volatility aligns with the first model prediction. I further explore heterogeneity of the correlation across firm characteristics and find empirical support for intuitive comparative statics additionally generated by the model.

Because the negative correlation cannot be interpreted causally, I employ an IV approach using firm-specific human capital, which I empirically approximate by the share of employees with vocational training (*vocational share*). The literature has discussed the role of firm-specific human capital in labor hoarding (Okun, 1963; Lindbeck and Snower, 2001), and my model conceptually suggests it as a suitable instrument. In the model, firms differ in how much they rely on firm-specific human capital in their production processes. When firms solely maximize expected profits, the reliance on firm-specific human capital shapes the capacity decision and, subsequently, labor hoarding, but does not affect the hedging decision. Firm-specific human capital impacts the capacity *and* hedging decision only through the trade-off induced by risk aversion, rendering it conceptually a valid instrument for hoarded labor. Empirically, I instrument hoarded labor with vocational shares, reflecting firms' technologies. The proxy is motivated by firms' investments in firm-specific knowledge during vocational training, with many apprentices being hired post-training (Dustmann and Schönberg, 2012). Consistent with the second model prediction, in the first stage, I find firms with a higher vocational share hoard more labor.

In the IV, I find a causal effect of labor hoarding on FX risk assumed by firms. Specifically, the two-stage least squares (2SLS) estimates in the baseline specification suggest a one-standard-deviation increase in labor hoarding reduces FX-induced CF volatility by 1.5 standard deviations. The observed increase in magnitude of the 2SLS estimates compared with the ordinary least-squares (OLS) estimates warrants a discussion. I reconcile the increase with the anticipated bias in the OLS stemming primarily from omitted-variable bias such as risk-management sophistication. Although I cannot rule out second-order direct effects of the instrument on the outcome, which may inflate the 2SLS estimates given the relatively low partial-R^2 values, weak-instrument-robust Anderson-Rubin tests across specifications strongly corroborate the existence of an effect. Various robustness checks, such as using an alternative measure for hoarded labor from STW during an eased-access episode in 2009 or using an alternative instrument based on the share of employees in shortage occupations, further support a causal effect of labor hoarding on FX risk assumed by firms.

To deepen the analysis of firms' FX-risk hedging in response to labor hoarding, I draw on two text-based measures for hedging, derived from hand-collected annual reports. Specifically, I construct a keyword-based measure to identify firms that use FX derivatives and an AI-based measure on active FX management more broadly. Using the first measure, I find (statistically weak) evidence that firms with more hoarded labor are more likely to use

FX derivatives. Results based on the second measure reveal the reduction in unhedged FX risk associated with labor hoarding is driven by firms that actively manage their FX exposure, alleviating remaining concerns around unobserved firm characteristics. To shed light on hedging strategies other than the use of FX derivatives, I manually classify operational hedging strategies for a subset of firms based on the five most relevant sentences from annual reports upon which the AI-based indicator is based.

This paper shows firm-specific human capital, resulting in labor hoarding, and the institutions that facilitate labor hoarding matter for firms' risk-taking in other areas. Risk plays a key role in the economy, and the capacity to assume risk has driven economic prosperity. Economies rely on institutions that incentivize individuals to engage in entrepreneurial activity by mitigating downside risks through insurance mechanisms. Against this background, the design of institutions is key for ensuring risk-taking is neither too excessive, jeopardizing the system's stability, nor subdued, hindering innovation and sectoral transformation. Thus, understanding how labor decisions and labor market institutions influence overall risk-taking in the economy is highly relevant, especially if firms' reliance on firm-specific human capital is expected to grow due to persistent labor shortages and growing specialization.

Related literature. The paper contributes to several strands of the literature. First, by introducing a new measure for labor hoarding, I contribute to the literature on the measurement of labor hoarding dating back to the 1960s (see Biddle (2014) for an overview). Previous research has used survey data (Fay and Medoff, 1985) or indirect methods (Fair, 1969; Clark, 1973; Rotemberg and Summers, 1990) to measure labor hoarding, but broad measurement at the firm level has proven difficult. Survey evidence on the use of STW during COVID-19, as in Kuhn, Luo, Manovskii, and Qiu (2023), strengthens the potential to learn about labor hoarding through STW usage – the approach explored in this paper.[3]

Second, it adds to the literature on the role of labor in the context of firm-level volatility. Prior studies have shown rigid wages for incumbent workers (Schoefer, 2021) and the inflexibility of labor expenses (Danthine and Donaldson, 2002; Donangelo, Gourio, Kehrig, and Palacios, 2019; Acabbi and Alati, 2021) amplify fluctuations in firms' CF.[4] The model in Bentolila and Bertola (1990) emphasizes the role of demand uncertainty in shaping firms' employment policies. More recently, Arellano, Bai, and Kehoe (2019) proposed a mechanism explaining why output and labor declined during the Great Recession while volatility, observed as dispersion in firm growth, increased. They argue demand volatility makes hiring

3 Kuo (2024) studies STW usage in Japan during the Great Recession in connection to labor hoarding.

4 The literature on labor-force heterogeneity and asset pricing has also highlighted that the negative relation between hiring and future stock returns is stronger for firms that rely more heavily on high-skilled labor (Belo, Li, Lin, and Zhao, 2017).

labor a risky endeavor, inducing firms to reduce their labor input in response to increased volatility. I introduce unused fixed labor and hedging of a second source of unrelated price uncertainty into a model framework similar to their example. I thereby, theoretically and empirically, connect the core mechanism to the firm level.

Third, I contribute to the literature on how firms respond to operating leverage from fixed labor by adjusting both the asset and liability side of their balance sheets. Whereas a large literature shows labor-induced operating leverage crowds out financial leverage (Simintzi, Vig, and Volpin, 2015; Serfling, 2016; Kuzmina, 2023; Favilukis, Lin, and Zhao, 2020),[5] the asset side – which is the focus of this paper – has received less attention. An exception is Ghaly, Anh Dang, and Stathopoulos (2017), who show firms that rely more on skilled labor hold higher levels of cash. This paper extends the analysis of asset-side adjustments, focusing on the role of hoarded labor, which is a downside *and* upside risk.

Fourth, this paper adds to a large literature on firms' hedging (Smith and Stulz, 1985; Froot, Scharfstein, and Stein, 1993; Stulz, 2024), in particular, their FX hedging (Alfaro, Calani, and Varela, 2024, 2021; Levin-Konigsberg, Stein, Averell, and Castañon, 2023; Eren, Malamud, and Zhou, 2023). Using hand-collected annual reports of private firms, I develop novel text-based measures to identify which firms hedge FX risk using operational and financial hedging strategies. This approach provides new insights into the prevalence of FX-derivatives use and active FX management, showing labor hoarding, driven by firm-specific human capital, is a determinant of hedging. Huang, Huang, and Zhang (2019) made a first step in this direction, examining how public firms' commitment to employee benefits, measured as an employee-treatment score, affects the proportion of foreign sales hedged with derivatives.

Fifth, I add to the literature on the role of firm-specific human capital (Becker, 1962; Lazear, 2009). Whereas the worker's perspective in this context has been studied, the firm's perspective has received less attention, with the exception of Jäger and Heining (2022), who exploit exogenous worker exits to study how firms respond to find a replacement for firm-specific human capital. I use firms' reliance on workers with firm-based vocational training and those in shortage occupations to proxy for firm-specific human capital. This approach is consistent with Jäger and Heining (2022), whose findings suggest higher replacement costs in thin labor markets. I connect firm-specific human capital to firms' decisions to hoard labor, a link already mentioned in Okun (1963) and further discussed in Hart and Malley (1996)

5 Corporate leverage is also impacted by workers' exposure to unemployment risk (Agrawal and Matsa, 2013), firms' dependence on talent (Baghai, Silva, Thell, and Vig, 2021), and unionization (Campello, Gao, Qiu, and Zhang, 2018; Schmalz, 2018). Financing constraints have been linked to labor hoarding (Giroud and Mueller, 2017) and to firing decisions (Caggese, Cuñat, and Metzger, 2019).

and Lindbeck and Snower (2001).[6]

The remainder of the paper is organized as follows. Section 2 presents and solves the model. Section 3 describes the data and section 4 describes and discusses the firm-level measure for hoarded labor. I present and discuss the negative correlation between labor hoarding and FX-induced CF volatility in section 5. Section 6 contains the results drawing on IVs. Section 7 examines how firms hedge FX risk. The last section concludes.

2 Mechanism in a Stylized Model

I build a stylized model that formalizes a labor-hoarding channel of risk management. The model has similarities to the example in Arellano, Bai, and Kehoe (2019) but innovates along three dimensions. First, it adds another price risk as an additional source of CF risk. Second, it explicitly models hoarded labor, allowing a close mapping to the data and the empirical setup later. Third, the model introduces firm-specific human capital as a dimension of firm heterogeneity to explain why firms choose different levels of hoarded labor.

The key risk trade-off in the model is the following, as illustrated in Figure 2. 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 increases expected CF but also increases the default probability. If the firm 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

6 In this respect, my paper is also connected to the recent literature on firms' talent hoarding (Haegele, 2022) and firms' internal labor markets (Cestone, Fumagalli, Kramaz, and Pica, 2015).

uncertainty. In $t = 1$, the firm receives *orders* $X \sim \mathcal{N}(\mu, \sigma^2)$.[7] 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 materializes 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.[8]

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

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

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

7 I 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.

8 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.

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.[9] 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 production and hoarded labor equals the size of the workforce; that is,

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

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.

9 I derive the model solution analytically for the constraint in (2). In the numerical simulation, I also consider the (more intuitive) constraint $P[CF_\gamma < 0] \leq \alpha$ (see Figure A.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.

2.2 Analytical Model Solution

I 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 B1. □

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

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

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

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

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

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

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

I briefly discuss the 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 B2. □

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. Figure A.1 illustrates the model solution for three increasing levels of γ (panels (a) to (c)). 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 B3. □

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, I numerically solve the model for a fixed set of parameters and derive testable predictions.

Panels (a) and (b) of Figure 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, I study how optimal choices of hoarded labor and the variance of the unhedged exchange rate change as a function of γ. Panels (c) and (d) of Figure 3 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.

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.*

I 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 3, Figure 4 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.

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 4, the unconstrained optimum with no hedging is feasible for more firms, weakening the relationship of interest.*

3 Data

This section describes the data sources and sample selection for the empirical analysis. The dataset at the Research Institute of the German Federal Employment Agency (IAB) is compiled from four main sources: novel establishment-level information on monthly STW receipt, matched employer-employee data, firm financial information from *Dafne* provided by Creditreform/Bureau van Dijk (BvD), and novel information on firms' FX hedging extracted from hand-collected annual reports using text analysis.

The dataset starts with the universe of German establishments that can be linked to a firm in Dafne. The confidential matching procedure used to link establishments to firms is detailed in Antoni, Koller, Laible, and Zimmermann (2018).[10]

10 See Jäger, Schoefer, and Heining (2021) and Moser, Saidi, Wirth, and Wolter (2021) for recent work with BvD data matched with German administrative data.

STW data. The dataset on STW receipt (*BTR KUG*) contains information on monthly STW usage from 2009 to 2020 (*Statistik der Bundesagentur für Arbeit: Tabellen, Realisierte Kurzarbeit, Nürnberg, Oktober 2021, Daten mit einer Wartezeit von bis zu 5 Monaten (ohne Hochrechnung)*). For each STW episode, I have the number of employees in STW, the shortfall in wages (in buckets), and the shortfall in hours in worker equivalents (in buckets; for details, see Appendix C3). I transform the data into a monthly panel and merge it with the Establishment History Panel (Ganzer, Schmucker, Stegmaier, and Wolter, 2023). This merge allows me to ensure basic consistency (see Appendix C1 for details) and add location and industry information. I aggregate the establishment-level data to the firm level, using the information from the largest establishment for location and industry.

Matched employer-employee data. I have employment histories since 2008 for all individuals employed at firms in the universe of linked establishments at any point since 2008 (*excerpt of Integrierte Erwerbsbiografien (IEB)*). Using standard procedures as described in Dauth and Eppelsheimer (2020), I take monthly snapshots to obtain monthly employment information and to calculate the share of employees per occupation per firm as of December 2019. These occupation shares are later used to construct IVs similar to shift-share instruments based on occupation characteristics.

Firm-level financial information. The data on firm financial information contain annual balance-sheet and income-statement information at the unconsolidated level and information on firms' relationship banks. I enhance these data with information on FX hedging, extracted from manually downloaded annual reports. Details on the text analysis and classification procedure underlying the hedging data are provided in Appendices C4 and C5.

Sample selection. I use the combined data to select the following sample of firms (see Appendix C2 for details). The starting point includes firms that report an income statement, specifically revenue, at the unconsolidated level in 2019 and 2020 (21,235 firms).[11] I exclude firms that are likely just holdings or fail basic data-consistency requirements similar to Kalemli-Ozcan, Sorensen, Villegas-Sanchez, Volosovych, and Yesiltas (2015), reducing the sample to 16,323 firms. I then match these firms with the confidential data at the IAB, with a successful match rate of 71%. I restrict attention to firms with at most 20 establishments (11,482 firms) and further to those firms where 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 firms in the sample primarily have employment in Germany. Following standard data-cleaning method-

11 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.

ology from the literature, I exclude regulated utilities (sections D and E of the Classification of Economic Activities (WZ 2008)), financial firms (section K), and firms in public service (section O), resulting in 9,145 firms. For the full sample, I restrict attention to firms with year-on-year revenue changes in 2020 above −20% or below 20%, resulting in 6,913 firms. For the sample of firms with FX data, I further focus on those that report FX transaction income in at least two years between 2010 and 2019 and for which I have information on their export share (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. The next section details how the labor-hoarding measures are constructed.

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, medium-sized firms that are technology leaders in a global niche market and have significant export activity. On average, firms with FX data are more productive (0.17 mil EUR vs. 0.13 mil EUR value added per employee), which is also reflected in higher average daily wages (52.80 EUR vs. 45.71 EUR). The selection bias toward higher-paying, more productive firms corresponds to a shift in industry composition (cf. Figure A.6) with the share of manufacturing firms doubling (62% vs. 32%). Thus, the subset of firms with FX data likely includes a higher proportion of so-called hidden champions. These firms in the tradable sector are typically less known ("hidden") but play a key role in the German economy where SMEs (*Mittelstand*) make up a large share of economic activity.

Additional data. To gauge service provision around FX derivatives, I use information on firms' relationship banks and hand-collected information on whether banks continued selling FX derivatives to clients in-house. I have information on firms' relationship banks provided by Creditreform, which I match to banks in SNL Fundamentals by name. Details on the data construction are provided in Appendix C6.

For a robustness check, I use novel individual-level data on STW usage (*Personen in Kurzarbeit (PRS KUG), Betaversion*, IAB), which contain for a subset of employees, information on benefit receipt per person.[12]

12 See Brinkmann, Jäger, Kuhn, Saidi, and Wolter (2024) for recent work with this data.

4 Measuring Firm-Level Labor Hoarding

I overcome the challenge of limited data availability on firms' temporarily underutilized labor by leveraging STW, a German labor market program, to construct a firm-level measure of hoarded labor. Although access to STW is usually highly restricted, these restrictions have been relaxed during certain episodes, during which a wide range of firms – including those with normal operations – became eligible. During these eased-access episodes, firms are incentivized to use STW, thereby revealing their temporarily idle labor, because benefit receipt requires detailed documentation of reduced working hours.

4.1 Institutional Setting: Short-Time Work in Germany

STW is designed to protect viable jobs at firms facing temporary external shocks (Cahuc, 2024). In this section, I provide institutional details on STW, including its operational procedures and access restrictions. Because the subsequent analysis focuses on the eased-access episode in the second half of 2020, I also present quantitative and qualitative evidence supporting the claim that access restrictions were temporarily lifted during this time.

STW is a policy scheme that 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% $\times$ 50%) STW benefits). Operationally, firms pay STW benefits to employees, and the employment agency later reimburses firms.

Firms apply for access (*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 per employee to be reimbursed. Payments from the employment agency are preliminary 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%.

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).

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. Figure 5 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.

Qualitative survey evidence corroborates the view that access restrictions were temporarily lifted in 2020.[13] An anonymized survey by proIAB among eight local employment agency branches on modified procedures in 2020, conducted in August 2022, reveals 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.

4.2 Construction of a Measure of Hoarded Labor

In the model, firms form expectations about the level of unused fixed labor associated with their employment decisions, based on the distribution of orders but without knowledge of actual monthly demand. An ideal measure of hoarded labor would thus capture firms' ex-ante choices of expected idle employee hours. Data availability for such a measure is very challenging, but STW during eased-access episodes allows for constructing a close measure.

I empirically construct a measure of hoarded labor as follows. The building block is firm-month-level data on the intensity of STW usage. I define *Unused Fixed Labor* of firm i in month m as

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

13 See also Bossler, Osiander, Schmidtke, and Trappmann (2023) and Kagerl (2024) for recent work on windfall effects of STW in 2020.

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 C3). I define the *STW Usage Intensity* for firm i, averaged across a set of months $\mathcal{M}$, as

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

I then define *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 in 2020, excluding the first lockdown period from March to May. As a robustness check, I construct a similar measure using data from 2009, averaging across the entire year.

I link STW usage intensity to year-on-year revenue changes to strengthen the interpretation of the measure. Specifically, the interpretation rests on the assumption that firms with similar output in 2020 as in 2019 also had comparable overall labor inputs and levels of temporarily underutilized labor in both years. Firms disclose their underutilization levels through STW during periods of eased access, but not at other times, because they would not qualify for the scheme then. I always control for the year-on-year change in revenue in 2020.[14]

4.3 Discussion of the Measure

I address the concern that the measure, based on 2020, primarily captures the impact of the COVID-19 shock by restricting the sample and presenting evidence suggesting STW usage in 2020 reflects more than the COVID-19 shock.

To reduce the COVID-19-driven STW usage embedded in the measure, I substantially restrict the sample in three ways. First, I exclude data from the lockdown months until May when constructing the measure (see (10)). Second, I restrict the analysis to firms with revenue in 2020 that is not too unusual (year-on-year revenue change in the range of $[-20\%, 20\%]$). Third, by requiring data on FX transaction income, I naturally focus on sectors like the tradable-goods sector, which are less reliant on personal interactions.

14 Year-on-year revenue changes serve as a proxy for output declines due to the COVID-19 shock, though they 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.

Next, I present multiple pieces of evidence indicating STW usage during the eased-access episode in 2020 reflects more than just the COVID-19 shock. First, STW was broadly used even among firms without a revenue drop in 2020. Figure 6 links STW usage in 2020 to year-on-year revenue changes, showing binned scatterplots of STW usage in panel (a) and of STW usage intensity in panel (b) against revenue changes. For firms that experienced a revenue drop (50% of the sample; see Figure A.3), STW usage is strongly associated with revenue changes. However, for firms with positive revenue growth, this association disappears, yet STW usage remains at approximately 20% for this group regardless of the level of revenue growth. In an analogous figure based on firms with FX data, this number is even higher at 30% (see Figure A.4). A similar pattern emerges for STW usage intensity in panel (b) of Figure 6.

Second, STW was broadly used even in months when industry-wide production was similar to production levels in 2019. In particular, I consider monthly industry-level revenue development rather than annual firm-level revenue development for the largest sectors in the sample. Figure 7 shows monthly industry-wide revenue (blue, LHS scale) and STW usage (red, RHS scale) for 2019 and 2020 in these industries. The figure shows that while economic activity largely recovered in the second half of 2020, STW-usage levels remained high. This finding further corroborates 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.

Third, the sample does not include sectors most impacted by the pandemic, such as food services. Specifically, the requirement for FX-data availability in analyses from section 5 onward shifts the focus away from sectors dependent on personal interactions toward the tradable sector, reducing the sample size by two-thirds (see panel (b) vs. panel (a) in Table 1). Figure A.6 compares the industry composition in the full sample with the sample with FX data. It reveals the largest sectors in the sample with FX data are manufacturing, trade, information and communication, and technical and scientific activities, further alleviating concerns about the influence of lockdowns on the measure.

Fourth, to underscore the uniqueness of the eased-access episode in 2020, I replicate Figure 6 using pooled data from years with regular access to STW as a placebo test. Figure A.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 previous scatterplots. 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, Figure A.7, 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).

4.4 Who Hoards Labor?

I use the new measure to shed light on the characteristics of firms that hoard labor. Panel (a) of Figure 8 illustrates the coefficients from a regression of labor hoarding on various firm characteristics, comparing firms within the same industry and region and controlling for revenue changes (see Table A.1 for the full regression results). No statistically significant differences exist between labor-hoarding and non-labor-hoarding firms in size, age, growth, and export share. However, labor-hoarding firms tend to be less productive,[15] as measured by value added per employee, and have higher leverage, although the latter finding is not robust across samples (cf. panel (b) of Table A.1). The lower productivity of labor-hoarding firms is a potential concern, which I address in subsequent analyses by controlling for value added per employee in robustness checks. This step reduces the sample size by one-third due to data limitations, however.

Panel (b) of Figure 8 compares workforce characteristics between labor-hoarding firms and their non-labor-hoarding counterparts. Employees show little difference in average age, wages, or tenure. However, in line with labor hoarding increasing operational leverage, labor-hoarding firms are more likely to employ workers on temporary contracts. They also have a larger share of employees with vocational training rather than college education, have a higher proportion of employees in shortage occupations, and score higher on a measure that reflects occupation-specific tenure weighted by firms' occupation composition. These workforce characteristics suggest labor-hoarding firms tend to have higher levels of firm-specific human capital, foreshadowing the analyses in section 6.

5 A Link between Labor Hoarding and Risk Management

Next, I link firms' labor hoarding to their risk management. Whereas labor-hoarding firms exhibit larger comovements of their CF with industry-level upturns and downturns, increased labor hoarding is not associated with higher overall CF volatility. Instead, and in line with the model predictions, I find more labor hoarding is negatively correlated with one specific

15 This finding is in line with the findings in Kagerl (2024).

contributor to CF volatility: FX risk. I argue FX risk is a particularly relevant and interesting source of CF volatility in the context of risk management and labor hoarding.

5.1 Labor Hoarding Increases Comovements with Demand Fluctuations

Labor hoarding impacts the fixed versus variable cost structure *and* is an implicit capacity choice with upside risk. To illustrate the upside potential of labor hoarding, I show in this section that the comovement of year-on-year changes in profitability with industry-wide upturns and downturns is stronger for labor-hoarding firms than for their non-labor-hoarding counterparts.

Whereas labor hoarding leads to idle labor and higher wage costs during periods of low demand, it also enables more production when operating at full capacity during periods of high demand. If not only an individual firm but also the entire industry is operating near its capacity limit, opportunities for price increases may arise (Boehm and Pandalai-Nayar, 2022). Thus, the additional production capacity facilitated by labor hoarding can enable firms to produce more output at higher prices during times of high demand, rendering these periods particularly profitable.

To empirically explore this upside potential of labor hoarding, I 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, I 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. I am interested in the coefficient β. *Labor Hoarding*$_i$ is a firm-level binary variable that takes the value of 1 if a firm engages in labor hoarding based on the measure defined in the previous section. The outcome of interest, Y_{it}, is annual profitability. I proxy year-on-year changes in demand at the industry level by using changes in the ifo Business Climate Index (6m-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).

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. I 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.

As a robustness check, I zoom in on the manufacturing sector and confirm the result proxying demand fluctuations by changes in orders at more granularly defined industry levels (available only for the manufacturing sector). Table A.4 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, I 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 Table A.4). Table A.3 corroborates the previous findings using this alternative proxy for demand fluctuations.

5.2 Total vs. Specific CF Volatility

Although labor-hoarding firms experience greater CF fluctuations in response to demand fluctuations, this section shows their overall CF volatility is not higher than for firms with less labor hoarding. Instead, firms with more labor hoarding exhibit lower CF volatility from unhedged FX risk.

To understand if labor-hoarding firms are riskier overall, I examine their total CF volatility. Specifically, I 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.

A binned scatterplot of total CF volatility against hoarded labor in panel (a) of Figure 9 shows firms with more hoarded labor do not exhibit larger total CF volatility. However, the correlation turns negative in panel (b). Panel (b) isolates a specific source of CF volatility, namely, from movements in exchange rates. FX-induced CF volatility is constructed similarly to total CF volatility using net FX gains instead of CF.

Although FX-induced CF volatility is defined formally below, the following example provides an intuitive illustration of what FX gains or 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.

Panel (a) of Table 3 formalizes the distinction between total and FX-induced CF volatility. Column 1 uses a binary variable, *Labor Hoarding*, whereas the other columns use the measure *Hoarded Labor* on the LHS. Value added per employee and ROA are included in columns 3 and 4 to control for differences in productivity, still yielding no statistically significant correlation with hoarded labor. A focus on FX-induced CF volatility shrinks the sample by two-thirds due to data availability (cf. panel (b) vs. panel (a) of Table 1). For firms with FX data, no statistically significant correlation of hoarded labor with total CF volatility exists, but does with FX-induced CF volatility (column 5 vs. column 6).

I construct two measures of FX-induced CF volatility from the accounting variables FX gains and FX losses following Adams and Verdelhan (2022).[16] I 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.

Panel (b) of Table 3 corroborates a negative correlation between hoarded labor and FX-induced CF volatility under both measures and varying sets of controls. Columns 3-6 add value added per employee to control for differences in productivity. Productivity matters for

16 They use the accounting variables for publicly traded firms, and I demonstrate the approach's applicability also to private firms because my sample contains almost only private firms.

the relationship of interest if more productive firms are less likely to use STW but more likely to export globally and be exposed to foreign currency, primarily USD, invoicing. Because value added is only available for a subset of firms, I use ROA as an alternative proxy for productivity in column 7. The negative correlation between hoarded labor and FX-induced CF volatility remains robust across specifications.

5.3 Why Focus on FX-Induced CF Volatility?

The risk trade-off studied in this paper is between hoarded labor related to demand uncertainty and hedging of a price risk. Firms typically face several types of price risks, such as fluctuations in input prices (e.g., material or logistics costs), output prices (e.g., competitive pressures, FX risk), customer default risk, or financing costs (e.g., interest rate risk). In this paper, I focus on FX risk from operations in foreign currency and argue in this section that it is particularly relevant in a labor-hoarding channel of risk management.

FX is a textbook example in risk management literature. In a recent overview article, Stulz (2024) defines a hedge as a "transaction that creates a gain for a corporation that offsets in part or in whole a loss that it incurs in its business activities" (p.11). FX risk is frequently used as an example because the underlying business risk is well identified, and financial hedging instruments, such as FX derivatives, are widely available. For instance, Bartram, Brown, and Fehle (2009) find FX derivatives are the most commonly used type of derivative used among non-financial firms.

FX risk presents a significant challenge for globally operating firms. This fact is illustrated for the firms in the sample in Figure 10, which 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 bil EUR in 2016 (see Figure A.9).

FX risk is particularly relevant in the context of labor hoarding among European SMEs. Among firms with FX data in the sample are likely many highly specialized manufacturing firms operating in global niche markets (see discussion in section 3). Their limited diversification exposes them to substantial idiosyncratic demand fluctuations. Thus, coupled with their global operations and likely substantial USD invoicing, the two key uncertainties (demand and price uncertainty) for a labor-hoarding channel of risk management play a particularly relevant role for them, making them ideal subjects for an empirical study focusing on the effects of labor hoarding. 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.

The accounting variables *FX Gains* and *FX Losses*, upon which FX-induced CF volatility is based, capture FX risk after hedging, aligning well with the model framework. To illustrate, suppose the firm in the example of the previous section 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.[17]

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 are shipped, further limiting the extent to which *FX Gains* and *FX Losses* fully capture overall FX risk.[18]

17 For further discussion, including on CF hedges and the case where the forward rate differs from the spot rate at the point of sale, see Adams and Verdelhan (2022). The latter case involves an economic loss equal to the difference between the spot rate at the point of sale and the forward rate.

18 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.

5.4 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, I examine heterogeneity of the correlation across firm characteristics. Columns 1 and 2 of Table 4 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, I 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. I 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 Table 4) 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 upward (downward in absolute terms, because the coefficients are negative).

6 Firm-Specific Human Capital as a Driver of Labor Hoarding

The negative correlation between labor hoarding and unhedged FX risk may be biased from various sources of endogeneity, for example, unobserved firm characteristics such as risk-management sophistication. Guided by the model, I instrument hoarded labor with firm-specific human capital, proxied by the share of employees with vocational training. I find a one-standard-deviation increase in labor hoarding reduces FX-induced CF volatility by 1.5 standard deviations and discuss the increase in magnitude compared with the OLS estimates. The effect remains qualitatively unchanged across robustness checks, including using the share of employees in shortage occupations as an alternative instrument.

6.1 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, with firms differing in their dependence on fixed labor. As shown in Lemma 1, when firms only maximize expected profits, the level of firm-specific human capital shapes their decision on how much fixed labor and subsequently hoarded labor to hold but has no bearing on the decision of how much exchange-rate risk to assume. The firm characteristic impacts hoarded labor *and* hedging only when the constraint binds. Subsequently, from a theoretical perspective, whereas firm-specific human capital drives the labor decision, it influences the hedging decision only through the trade-off induced by risk aversion.

I use the firm-level share of employees with vocational training as a proxy for firm-specific human capital. Employees with vocational training have completed firm-based on-the-job training as part of apprenticeship schemes, which are supplemented by classes at vocational schools once or twice a week. An apprenticeship typically lasts two to three years and concludes with a final examination. During firm-based vocational training, firms have an incentive to invest in developing firm-specific knowledge and skills. Dustmann and Schönberg (2012) argue Germany's vocational training is successful because it occurs within firms, not just at vocational schools. Firms know and invest in the skills necessary in the workplace, motivated by the likelihood of hiring their apprentices post-training. Survey evidence shows firms are willing to offer employment contracts to apprentices in about 90% of cases (Mohr, 2015).

I estimate the following 2SLS specification:

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

with $\mathbf{X}_i$ a vector of control variables based on 2019 and fixed-effect dummies (industry by region). *Share Vocational Training* is calculated in 2019, but, as discussed further below, the share is highly stable across the years.[19]

19 The IV is potentially a mismeasured IV because I only proxy for firm-specific human capital. However, mismeasurement of the instrument does not invalidate the design in a classical measurement-error setting. To see this, let $Z_i = Z_i^* + e_i$ be the mismeasured instrument and let Z_i^* be the true instrument with e_i, the measurement error. I argue $E[Z_i^* \varepsilon_i] = 0$, but eventually impose $E[Z_i \varepsilon_i] = 0$ in the estimation procedure. However, if e_i is independent from ε_i, $E[Z_i \varepsilon_i] = E[Z_i^* \varepsilon_i] + E[e_i]E[\varepsilon_i] = 0$, so the mismeasured instrument remains valid.

Instrument validity hinges on the standard relevance and exclusion restriction. Regarding relevance, I expect a higher share of employees with vocational training to be associated with a higher level of hoarded labor. Regarding relevance, the bottom of Table 5 reports the estimated first-stage coefficient, α, which is positive as hypothesized. The magnitude of the coefficient implies a 100-basis-point increase in the share of employees with vocational training is associated with a 26-basis-point higher fraction of the workforce that is temporarily idle. The resulting first-stage F-statistic (Kleibergen-Paap Wald statistic; see Andrews, Sock, and Sun (2023)) is 15.15 and passes the Stock and Yogo (2005) threshold for weak instruments.

The exclusion restriction demands that the correlation between the endogeneous variable and ε_i only stems from η_i. In other words, it demands that, after conditioning on controls, the instrument is uncorrelated with unobserved variables relevant for the relationship of interest in (R3). The exclusion restriction would be violated, for example, if firms' exposure to global markets, and thus their CF volatility due to exchange-rate movements, shapes their technology and, as a result, their demand for employees with vocational training. Or, it would be violated if training people in a certain occupation is additional risk that is hedged elsewhere, for example, via FX-risk hedging. To alleviate this concern, as before, I compare firms in the same industry and region and control for size, export share, and exposure to the COVID-19 shock (revenue change).

I provide two additional pieces of support for the exclusion restriction. Table A.5 shows firms with an above-median share of employees with vocational training are indistinguishable in means by size and export activity from firms with a below-median share. Although this is not the case for all characteristics, in an alternative specification including industry-by-region fixed effects (Table A.6), I find the share of employees with vocational training significantly correlates neither with ROA nor with the propensity to export to destinations outside Europe. The share with vocational training still correlates with the cash-to-assets ratio and value added per employee, and I control for the latter in a robustness test.

Second, for the subset of firms for which I have annual information on foreign revenue, I exploit the panel dimension of the information on employees with vocational training. Table A.7 shows the share with vocational training is not correlated with the export share when including firm and time fixed effects. Importantly, including firm fixed effects explains almost all variation in the share with vocational training, suggesting the latter is stable over time. This finding supports the idea that firms' fixed technology drives their employment composition across employees with or without vocational training.

6.2 Impact of Labor Hoarding on Unhedged FX Risk

Figure 11 illustrates the IV design, depicting the first stage in panel (a), the second stage in panel (b), and the reduced form in panel (c). The visualization already points toward the existence of a causal effect of labor hoarding on unhedged FX risk assumed by firms, which I now test more formally.

Panel (a) of Table 5 shows the baseline specification (columns 3 and 4) alongside the OLS (columns 1 and 2) and reduced-form estimates (columns 5 and 6). The size of the 2SLS estimates suggests a one-standard-deviation increase in hoarded labor reduces FX-induced CF volatility by 1.5 standard deviations (= $(18.43 \times 0.05)/0.62$). The estimates for both measures of FX-induced CF volatility are similar in magnitude, and the statistical significance of the reduced-form estimates additionally supports a causal link. The 2SLS estimates change little when controlling for productivity, analogously to before, in panel (b). In all specifications, the first-stage F-statistic is sufficiently large.

Discussion of the increase in coefficient magnitude. Relative to the OLS estimates, the IV estimates in Table 5 increase by an order of magnitude, warranting a further discussion in which I focus on the following three points. First, following the steps suggested in Jiang (2017), I reconcile the larger magnitude of the 2SLS estimates relative to the OLS estimates with the bias anticipated in the OLS. The two primary endogeneity concerns in the OLS were omitted-variable bias and reverse causality. Reverse causality – such as firms with lower FX risk portfolios having greater flexibility to hoard labor – would bias OLS estimates downward (or upward in absolute terms, because the coefficients are negative). Omitted-variable bias, such as sophistication in risk management, would bias the OLS upward (downward in absolute terms), because firms with advanced risk-management practices likely experience both reduced employee downtime and lower unhedged FX risk. The relative magnitudes of the OLS and IV estimates suggest an omitted-variable bias outweighs reverse-causality concerns. This aligns with the observed weakening of the effect for firms with more than three relationship banks, a proxy for risk-management sophistication (see the discussion in the previous section).

Second, also following the points outlined in Jiang (2017), I examine potential amplification effects. Jiang (2017) argues a design may suffer from small partial R^2 of the excluded instruments in explaining variation in the endogenous variables, which potentially creates a weak-instrument issue despite a sufficiently large first-stage F-statistic.[20] This scenario may lead to blown-up estimates if even a small second-order direct effect of the instrument on the

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

outcome exists. The bottom rows of Table 5 show the partial R^2 of the excluded instruments for explaining variation in hoarded labor. The 2SLS estimates are indeed smaller (-13.77/-15.22 in columns 1 and 3 of panel (b) vs. -18.43/-20.12 in column 3 of panel (a) and column 5 of panel (b)) in specifications with a partial R^2 of an order of magnitude larger (0.11/0.22 vs 0.005/0.004). Because potential second-order direct effects of the instrument on the outcome cannot be ruled out, this finding does not fully alleviate concerns such effects may contribute to the magnitude of the 2SLS estimates.

Third, I report the results of the weak-instrument-robust Anderson-Rubin test in the bottom rows of Table 5. The very small Anderson-Rubin χ^2 p-values corroborate the existence of a causal effect of hoarded labor on FX risk.

Robustness. I conduct three further robustness tests. First, in panel (a) of Table A.8, I replicate the analysis using an analogously constructed measure for hoarded labor based on the 2009 eased-access episode. I control for exposure to the Global Financial Crisis through the year-on-year revenue change in 2009, as well as firm size and export share. The robustness check also addresses measurement concerns, because hoarded labor measured this way predates the period used to calculate FX-induced CF volatility (2010-2019). The OLS estimates remain of a similar magnitude to before, reducing concerns around reverse causality. In columns 3 and 4, I use the share of employees with vocational training in 2008 as an instrument for hoarded labor, which yields positive first-stage coefficients. The 2SLS estimates are negative and statistically significant, but the small first-stage F-statistics warrant some caution. Nevertheless, Anderson-Rubin χ^2 p-values are very small, supporting the existence of an effect.

In a second robustness test, I 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.[21] I categorize firms based on text data about their export destinations, provided by BvD. Following Gopinath and Itskhoki (2022), I assume exports within Europe (excluding the UK) are denominated in euro, while USD is the dominant currency for exports outside Europe. Panel (b) of Table A.8 shows that, although the direction of the effect remains, its statistical significance weakens. However, the sample is reduced by more than half. The fact that more than 80% of firms with export-destination

21 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 finding aligns with the assumption that USD is the dominant currency globally, because approximately 70% of German exports are within Europe and are likely euro-denominated. I categorize a firm as exporting outside the euro area if it lists at least one export destination outside of Europe.

data export to outside the euro area (see Table 1) suggests such exports play a major role in the unrestricted sample as well, enhancing its credibility.

Third, I use an alternative proxy for firm-specific human capital based on occupation-specific tenure, similar to a shift-share instrument. Worker tenure reflects experience and has traditionally been used as measure for human capital. However, relying solely on average employee tenure may not be ideal, because longer tenure could also signal rigidity and reduced innovation. To mitigate this concern, I calculate the average share of employees within each occupation who have been with their employer for more than 10 years, capturing occupation-specific tenure. I then construct a firm-level measure by weighting the share of employees in each occupation by this occupation-specific tenure metric. The resulting firm-level index has a correlation coefficient of 0.53 compared with the previous instrument. As shown in Table A.11, the first-stage F-statistic decreases across specifications, and the statistical significance weakens. However, the direction of the effect remains consistent.

To examine whether other risk-management tools moderate the results, I investigate heterogeneity of the effect with respect to liquidity. However, Table A.12 shows no significant difference in the effect between firms with high or low cash-to-assets ratios.

6.3 Labor Market Shortages

Using firm-specific human capital as an instrument for hoarded labor hinges on firms' inability to hire employees with specialized tasks on short notice, which motivates the share of employees in hard-to-replace occupations as an alternative instrument in this section. Suppose firms' fixed technologies determine their need for employees across occupations. Also suppose occupations differ in the length of time required, to find, hire, and train a suitable candidate for specialized tasks. If this time exceeds the forecast horizon for demand, the firm must hire employees in that occupation in advance.

Empirically, I calculate the share of employees in firm i in occupation j as of December 2019 ($\textit{Share Occupation}_{ij}$) and draw on a classification by the Federal Employment Agency of which occupation is a so-called shortage occupation (clasification as of December 2019).[22] I define $\textit{Shortage Share}_i$ as

$$\text{Shortage Share}_i = \sum_j \text{Share Occupation}_{ij} \cdot \mathbf{1}(\text{Occupation j is Shortage Occupation}),$$

22 I use the most granular occupation information (5-digit occupations). More details on the classification procedure can be found here: `https://statistik.arbeitsagentur.de/SiteGlobals/Forms/Suche/Einzelheftsuche_Formular.html?nn=20626&topic_f=fk-engpassanalyse`.

where $\mathbf{1}(\cdot)$ is an indicator function that equals 1 if occupation j is classified as a shortage occupation.

The definition of shortage occupations by the Federal Employment Agency 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 experts 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 unique to individual firms, such as poor working conditions or limited mobility among the unemployed. I supplement the federal-level data with additional information at the regional level (*Bundesland*).

Similar to the previous instrument, the relevance condition requires that a higher share of employees in shortage occupations induces firms to hoard more labor, because they cannot hire in these occupations on demand. The bottom of Table 6 reports the coefficient from the first-stage regression of hoarded labor on the shortage share, showing a positive association. The associated first-stage F-statistic is 12.29 in the baseline specification and thus passes the threshold for weak instruments.

Regarding the exclusion restriction, firms with an above-median shortage share are, on average, similar in size-related measures such as assets and revenue than firms with a below-median shortage share (see Table A.9). The two groups do not differ significantly in characteristics such as leverage and ROA, but in others, such as the cash-to-assets ratio and value added per employee. I account for value added per employee in a robustness check (columns 3-6 of Table 6). Additionally, firms with a higher shortage share tend to have higher average export shares. However, a separate analysis (Table A.10) confirms the shortage share is not correlated with the likelihood of exporting outside of Europe after including industry-by-region fixed effects.

Table 6 presents the results using the shortage share as an instrument for hoarded labor, corroborating the existence of an effect of hoarded labor on FX-induced CF volatility. The magnitude of the 2SLS estimates is reduced by about two-thirds, consistently across specifications. The results show little change when both instruments are included in Table A.13. The overidentification tests in the baseline specifications pass at the 10% level.

7 FX Hedging

Next, I deepen the analysis of firms' FX-risk hedging in response to labor hoarding by constructing two text-based measures for hedging derived from hand-collected annual reports. The first measure is keyword-based and identifies firms that use FX derivatives, whereas the second measure is AI-based and identifies firms with active risk management more broadly. I uncover, first, that firms with more hoarded labor are more likely to use FX derivatives. Second, by exploring heterogeneity of the 2SLS estimates by whether firms are identified as actively managing FX risk, I show the effect is largely driven by firms that actively manage their FX exposure.

7.1 Use of FX Derivatives

Using a keyword-based measure based on hand-collected annual reports, I first present stylized facts on firms' use of FX derivatives. 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 C4 for details). Approximately 25% of firms in the sample are identified as FX-derivatives users.[23] These firms are larger across all size measures (Table A.14), with the median user being 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.

I find suggestive evidence that FX-derivatives usage is targeted more toward exports than imports. Table A.15 explores the connection between FX-induced CF volatility and the export share in panel (a) and the import share in panel (b). The export share is strongly correlated with FX-induced CF volatility but less so for derivatives users, as shown by the negative interacted coefficient in column 1 of panel (a). Due to data availability, the sample substantially shrinks when including the import share as a control (column 2). 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 (b).

To understand the role of FX-derivatives usage, I investigate whether firms with higher levels of hoarded labor are more likely to use FX derivatives. To that end, I use the keyword-based measure of derivatives usage as an outcome variable. Columns 1-3 of Table 7 report the results from a logistic regression model with varying fixed effects, whereas columns 4 and 5

23 Some firms explicitly mention they do not use FX derivatives. Thus, a non-user is a firm that either does not mention or negates the usage of FX derivatives.

show the results from OLS and 2SLS regressions, using the vocational share as an instrument for hoarded labor. The positive, albeit statistically weak, coefficients suggest labor hoarding increases the propensity to use FX derivatives, supporting the hypothesis that labor hoarding influences risk-management decisions.

I examine how the effect varies based on the quality of FX-hedging services provided by firms' relationship banks. The proxy for FX-service quality leverages the introduction of the European Market Infrastructure Regulation (EMIR) in 2014.[24] This regulation increased reporting requirements for both firms and banks, leading to significant consolidation among local banks offering FX derivatives (see Figure A.8). Against this background, I assume banks that continued to offer FX derivatives after the introduction of EMIR have it as a central part of their business and provide high-quality in-house services. A firm is classified as having access to high-quality FX services if it is connected to one of these local banks. The data are derived from hand-collected annual reports of over 800 German banks, from which I extract annual information on their FX-derivatives positions with clients (see Appendix C6 for details). However, Table A.16 shows no statistically significant heterogeneity along this dimension.[25]

7.2 Operational vs. Financial Hedging

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, I apply AI to analyze the risk-management sections of appendices in annual reports to determine whether a firm actively manages FX risk (see Appendix C5 for details). According to the 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 the previous results are primarily driven by firms that actively manage FX risk. Table 8 presents the OLS and 2SLS estimates, allowing for heterogeneity based on the AI-generated classification. Albeit not beyond 10 individually, the first-stage F-statistics for the main effect and interaction effect are sizeable. The 2SLS

24 Following EMIR's introduction in 2014, the costs of using FX derivatives increased. This was primarily due to the need for costly identification numbers and additional back-office capacity for new reporting requirements. Firms could delegate newly introduced reporting requirements to banks, which also faced increased infrastructure demands. For many local banks (savings and commercial banks), FX derivatives were previously the most important type of derivatives sold to customers and a core part of their business.

25 The quality of the proxy may be worse than hoped for, as the text in banks' annual reports suggests that several banks started commissioned trading or delegated their customers to other banks within the banking groups. This is in line with Figure A.9 where there is no discernible drop in outstanding amounts in 2014 per banking group.

estimates in columns 3 and 4 show the effect largely stems from firms that actively manage their FX risk, alleviating remaining concerns about unobserved firm characteristics behind the results.

To qualitatively understand which operational hedging strategies firms employ, I 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. I focus on firms the AI flagged as actively managing FX risk, examining 175 firms from a random sample of 500.[26] Figure 12 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 explicitly mentioned. Some firms also mitigate exposure by using increased mark-ups or price-adjustment clauses for transactions invoiced in foreign currency.

8 Conclusion

This paper provides evidence on the role of hoarded labor in firms' risk management. I develop a firm-level measure of hoarded labor using German administrative data on STW, combined with matched employer-employee data and firm financial information. Consistent with the risk trade-off formalized in the model, I show firms reduce FX risk in response to more labor hoarding. The IVs, used in this paper, which proxy for firm-specific human capital, are informative in themselves, because they emphasize the role of labor market rigidities in the mechanism.

Regarding specific policy implications, this paper provides another justification for non-financial firms' easy access to financial hedging tools such as FX derivatives. In the wake of post-crisis derivatives market regulation, the ability of non-financial firms to access derivatives markets, which are typically dominated by large financial institutions, has been a subject of debate. Generally, reducing barriers for firms to utilize low-distortion hedging tools, that is,

26 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.

hedging tools with minimal impact on other firm choices, is advantageous. The findings in this paper indicate hoarded labor prompts firms to mitigate other business risks, highlighting rigidities in the labor market as an additional rationale for facilitating non-financial firms' access to hedging tools.

More broadly, these findings are a potential starting point for future research on firms' risk-taking in the context of labor and financial market institutions. Although the capacity to assume risk has driven economic prosperity, risk-taking must not compromise system stability. Economies rely on institutions that incentivize individuals to engage in entrepreneurial activity by mitigating downside risks through insurance mechanisms. This paper shows the costs of hoarding labor and institutions that facilitate labor hoarding matter for firms' risk-taking in other areas. Because firms' reliance on firm-specific human capital may increase due to persistent labor shortages and growing specialization, understanding how these institutions affect overall economic risk-taking becomes particularly important.

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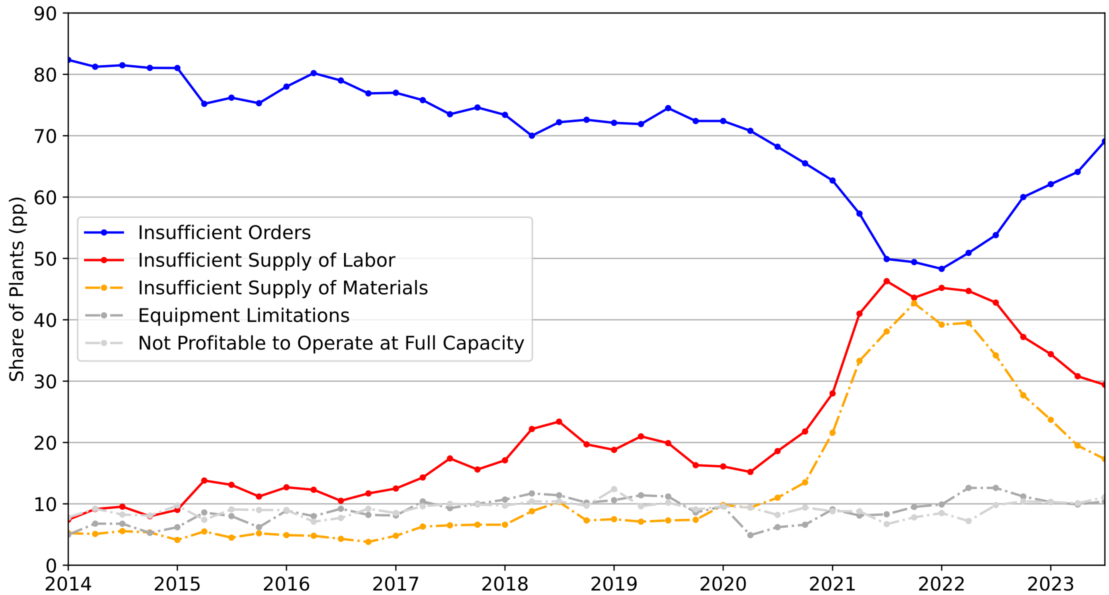
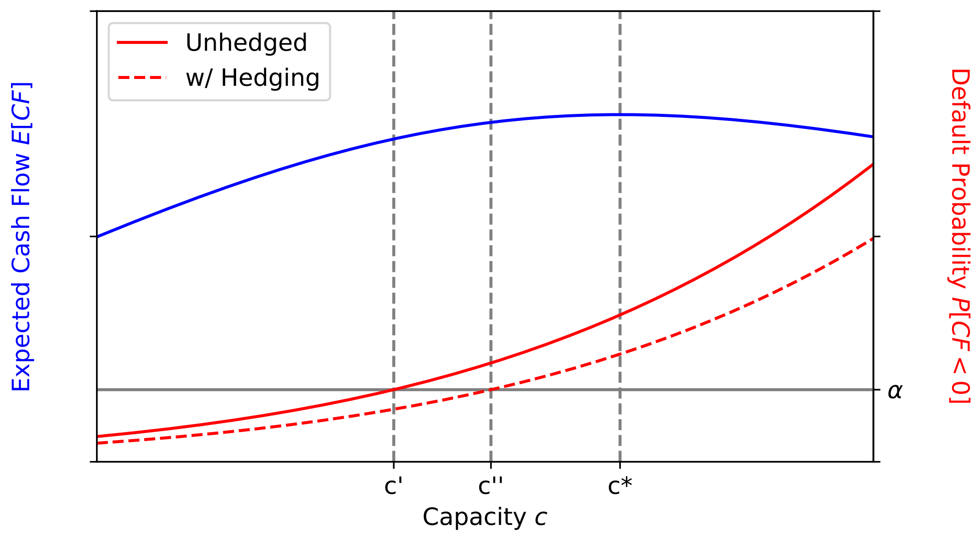
Figures

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



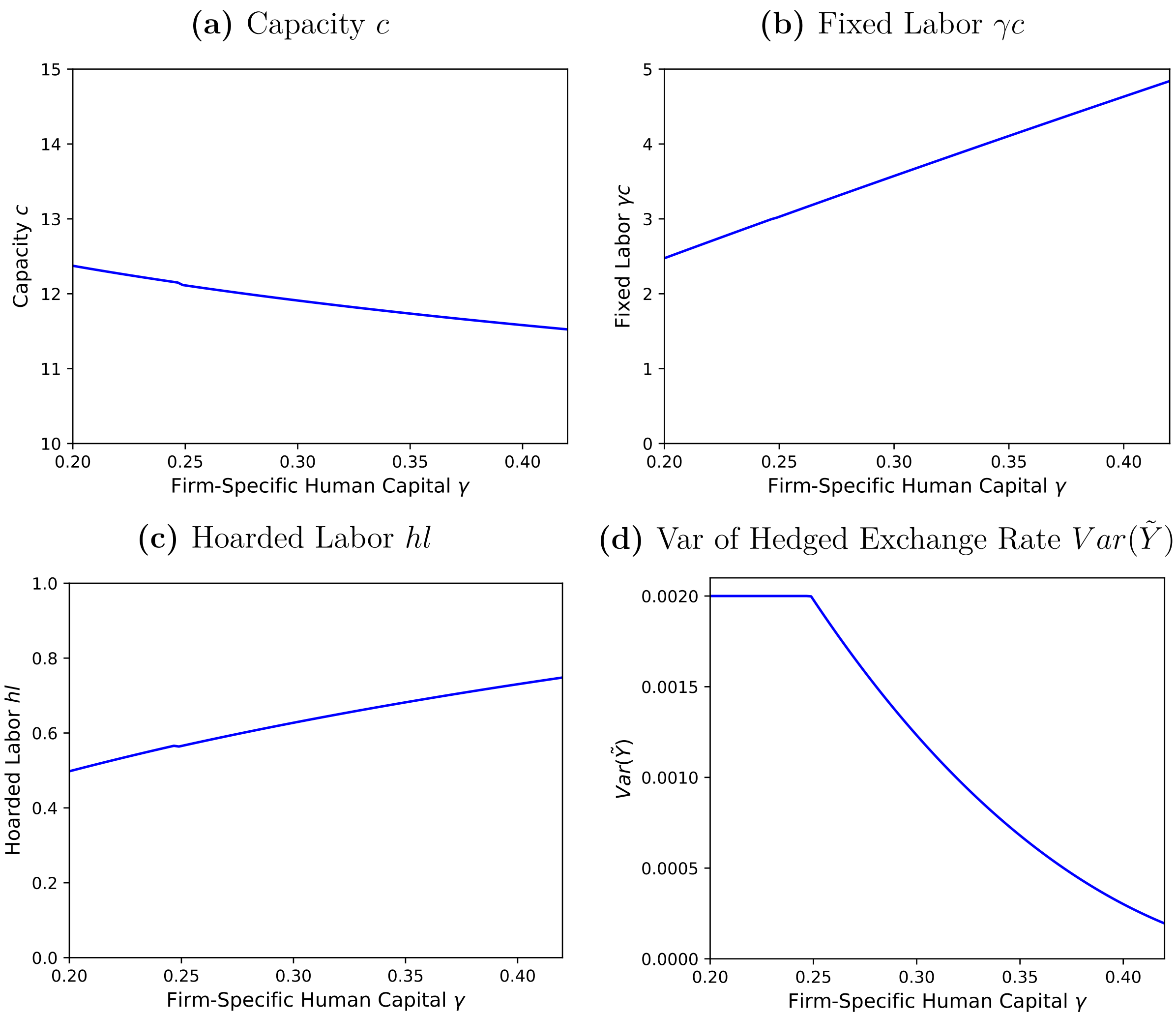
Notes: The figure shows the share of plants, among those with reduced production, that indicate each reason as a primary reason for actual production being below full production capability. The data is quarterly. Multiple answers are possible. The data source is the Quarterly Survey of Plant Capacity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

Figure 2: Model: Core Trade-Off



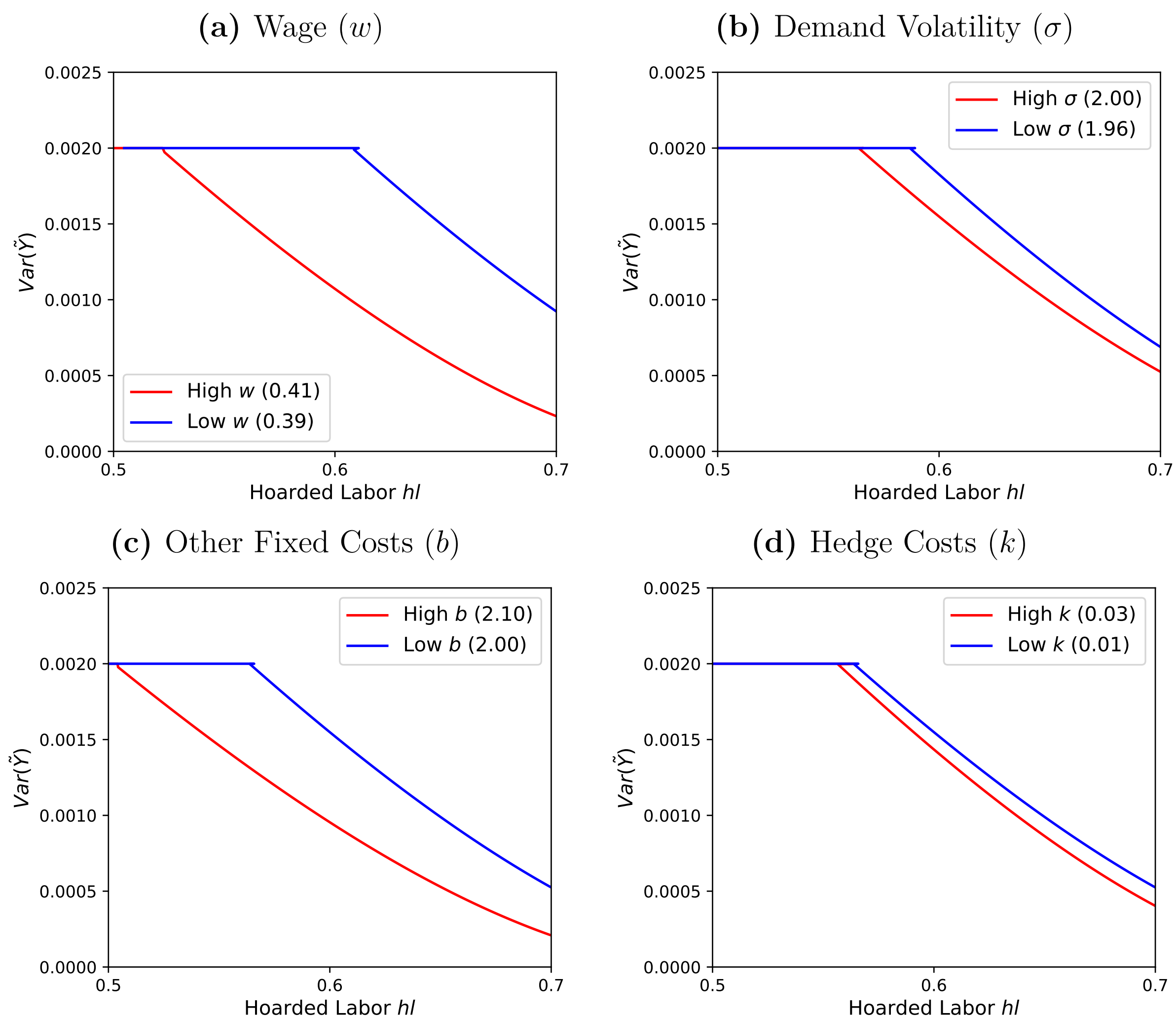
Notes: The figure illustrates, for a fixed level of firm-specific human capital γ, the core trade-off around the choice of fixed labor (γc) between expected cash flow (blue, LHS scale) and default probability (red, RHS scale). c^* denotes the optimal capacity choice in the absence a cap on the default 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.

Figure 3: Model: Outcomes As Functions of Firm-Specific Human Capital



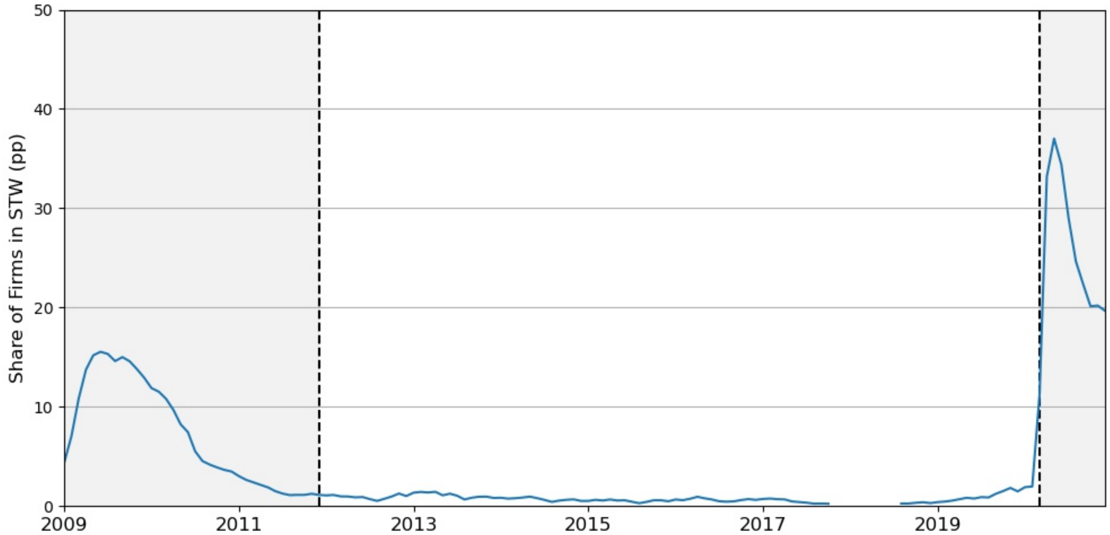
Notes: The figure shows how optimal *capacity*, c, in panel (a), *fixed labor*, γc, in panel (b), *hoarded labor*, $hl = \gamma(c - E[\min(X, c)])$, in panel (c), and the *variance of the hedged exchange rate*, $Var(\tilde{Y}) = 2p(a-h)^2$, in panel (d) change as a function of firm-specific human capital γ. The constraint considered is $P[CF < 0|Y = (1-a)] < \alpha$. 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 4: Model: Comparative Statics



Notes: The figure shows comparative statics in w, σ, b, and k 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: $\mu = 10, \sigma = 2, b = 2, a = 0.1, p = 0.1, w = 0.4, \alpha = 0.01, k = 0.01, q_{min} = 0.02$.

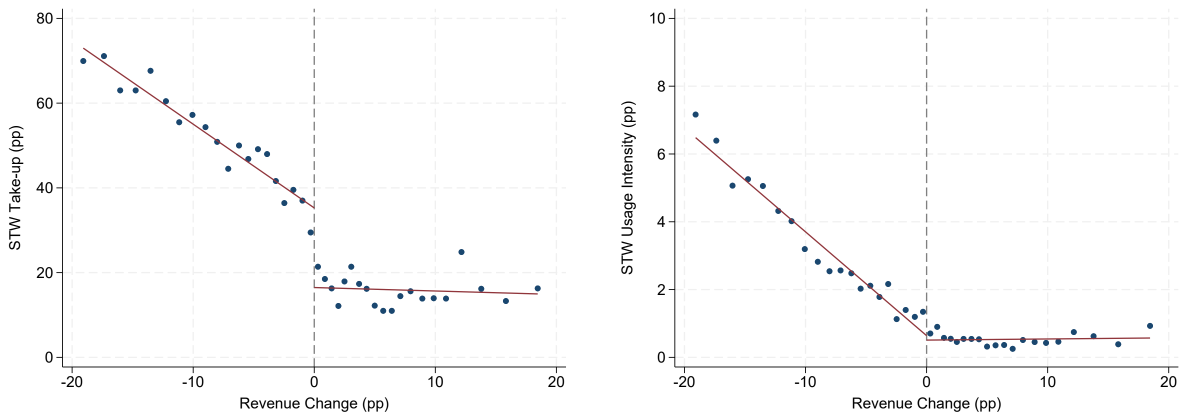
Figure 5: STW Usage and Eased Access Over Time



Notes: The figure 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). The gap in the data series comes from data protection (fewer than 20 firms). The sample consists of all firms with available revenue information in 2019 and 2020 that can be matched reasonably well to the administrative employment data at the IAB (9,145 in 2020) (see section 3 for details).

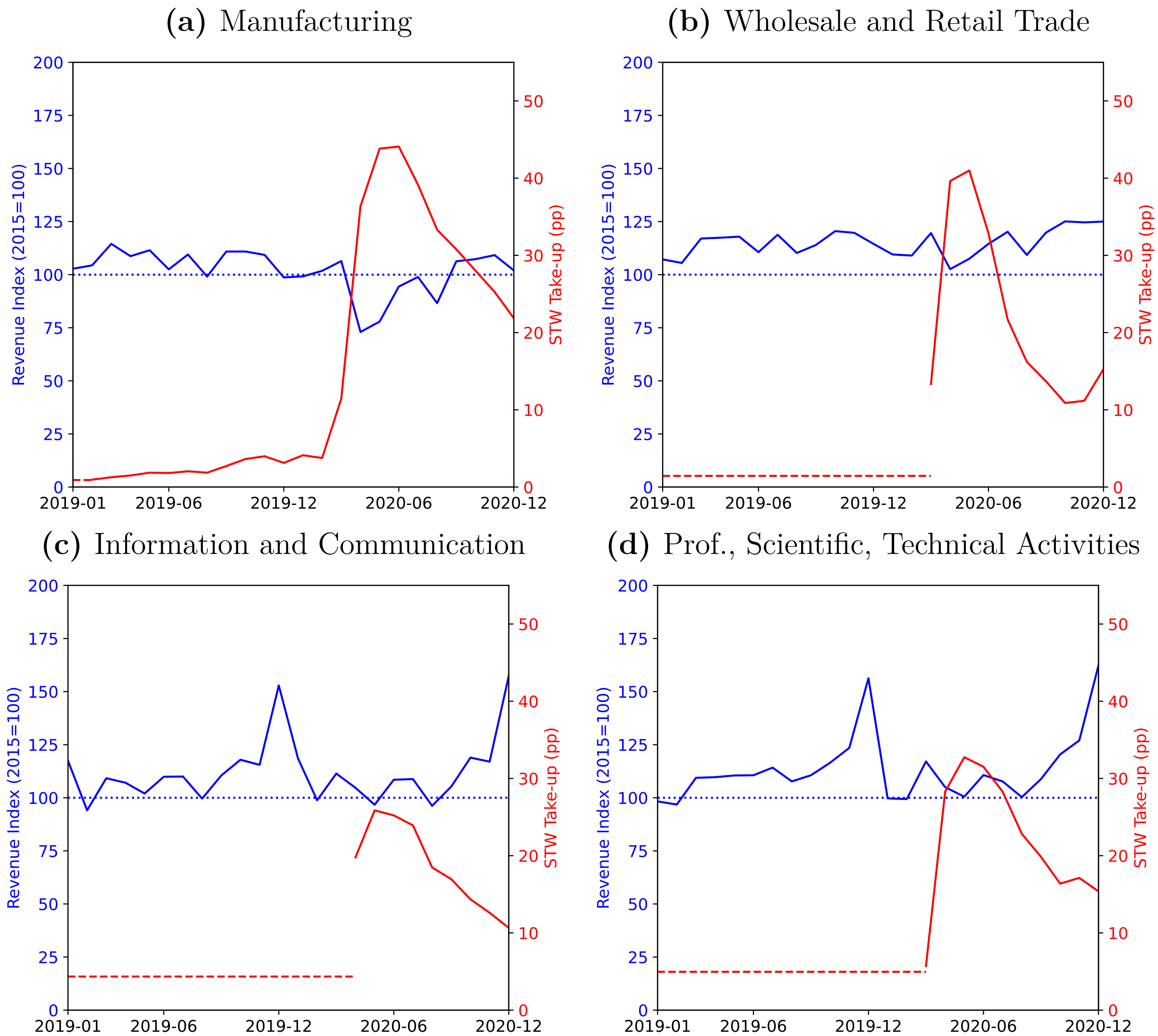
Figure 6: STW Usage by Firm-Level Revenue Change

(a) STW Take-Up **(b)** STW Usage Intensity



Notes: The figure shows binned scatterplots of STW take-up in panel (a) and of the STW usage intensity in panel (b) against the year-on-year revenue change 2020 (in pp). The results are based on the full sample of firms (see panel (a) of Table 1). The time window considered for STW take-up (binary) and STW usage intensity is June until December 2020, thus excluding the lockdown months until May. STW usage intensity is defined as the average monthly worker-equivalent of the reduction in work relative to employment (for details see section 4.2).

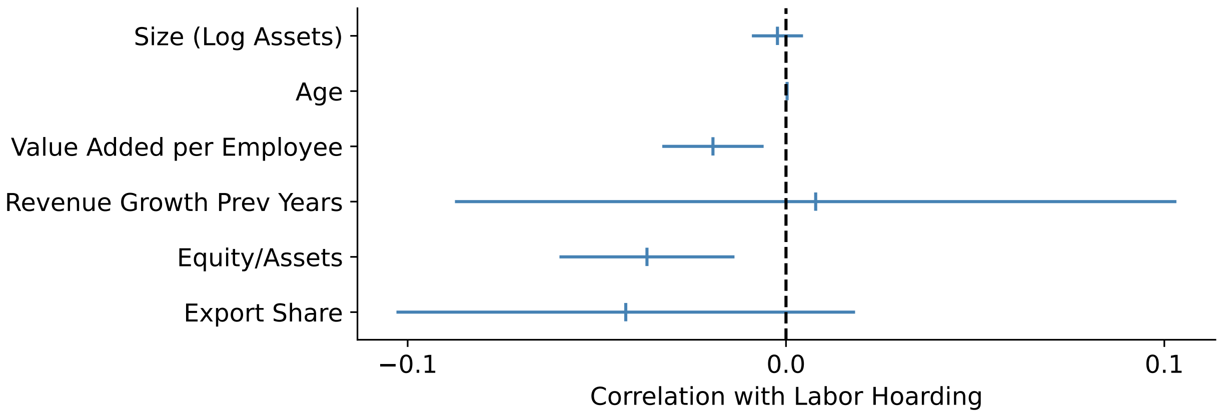
Figure 7: STW Usage Over Time vs. Industry-Level Revenue



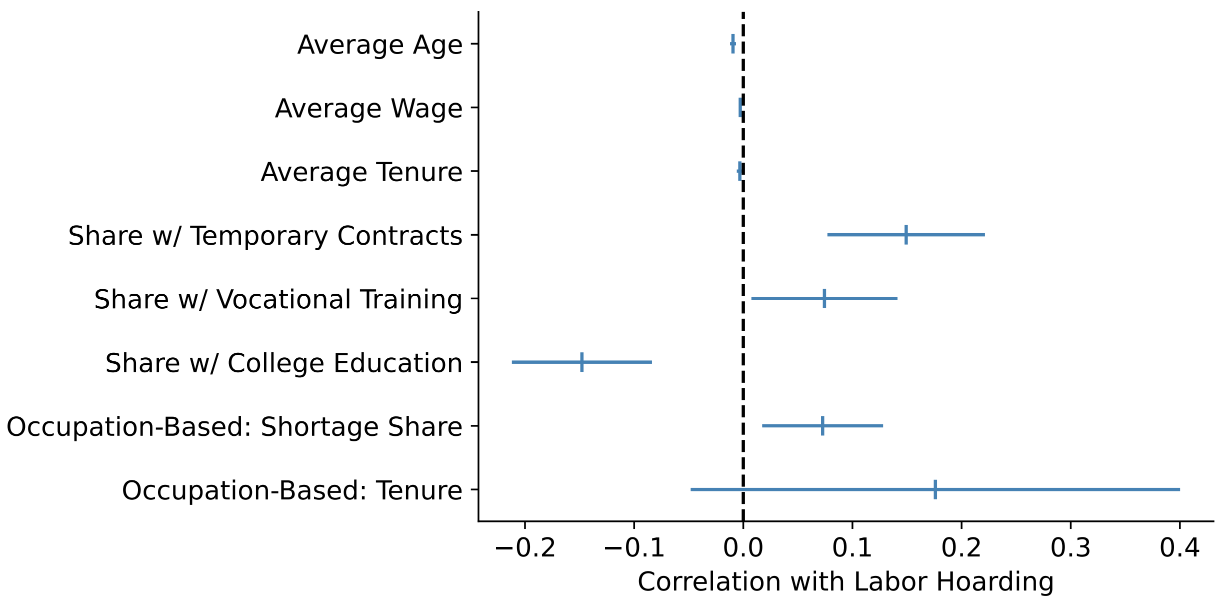
Notes: This figure plots industry-wide revenue (blue, LHS scale) against the share of firms in STW per industry (red, RHS scale) for the four largest industries (see Figure A.6). The frequency of the data is monthly. Revenue is a value index, normalized to 100 in 2015 (raw series), from the Federal Statistical Office of Germany (tables 42152-0001, 45212-0005 and 47414-0005). For the time series of STW usage, no data is available below the dotted red line per industry due to data protection. The results are based on the full sample of firms (see panel (a) of Table 1).

Figure 8: Who Hoards Labor?

(a) Firm Characteristics

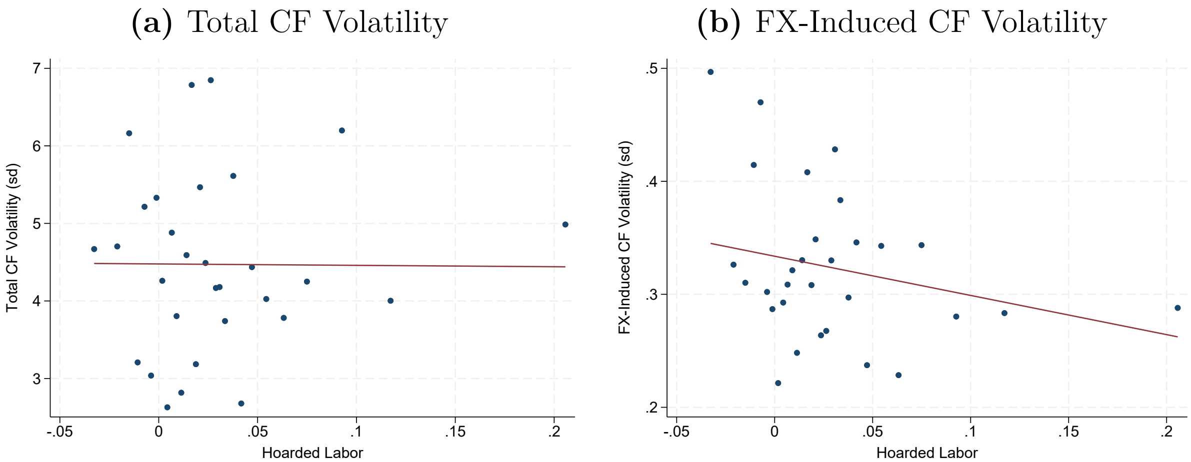


(b) Workforce Characteristics



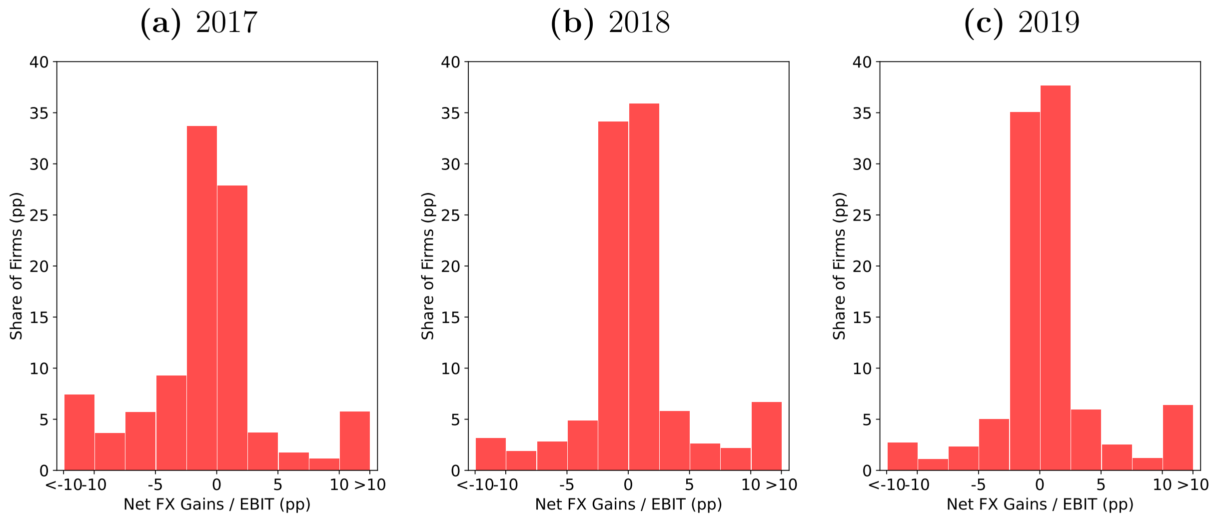
Notes: The figure shows the estimated OLS coefficients and 95% confidence intervals of a regression of *Labor Hoarding* on firm characteristics in panel (a) and on workforce characteristics in panel (b). *Labor Hoarding* is a binary firm-level variable that takes the value of 1 if the firm uses STW in the eased-access episode in 2020 (June-December), for details see section 4.2. See Tables A.1 and A.2 for the full regression tables. 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*). *Revenue Growth Prev Years* is the constant average growth rate of revenue between 2015 and 2019. Workforce characteristics are as of 2019. For details on *Occupation-Based: Shortage Share* and *Occupation-Based: Tenure* see sections 6.3 and 6.1.

Figure 9: Link between Labor Hoarding and Cash Flow Volatility



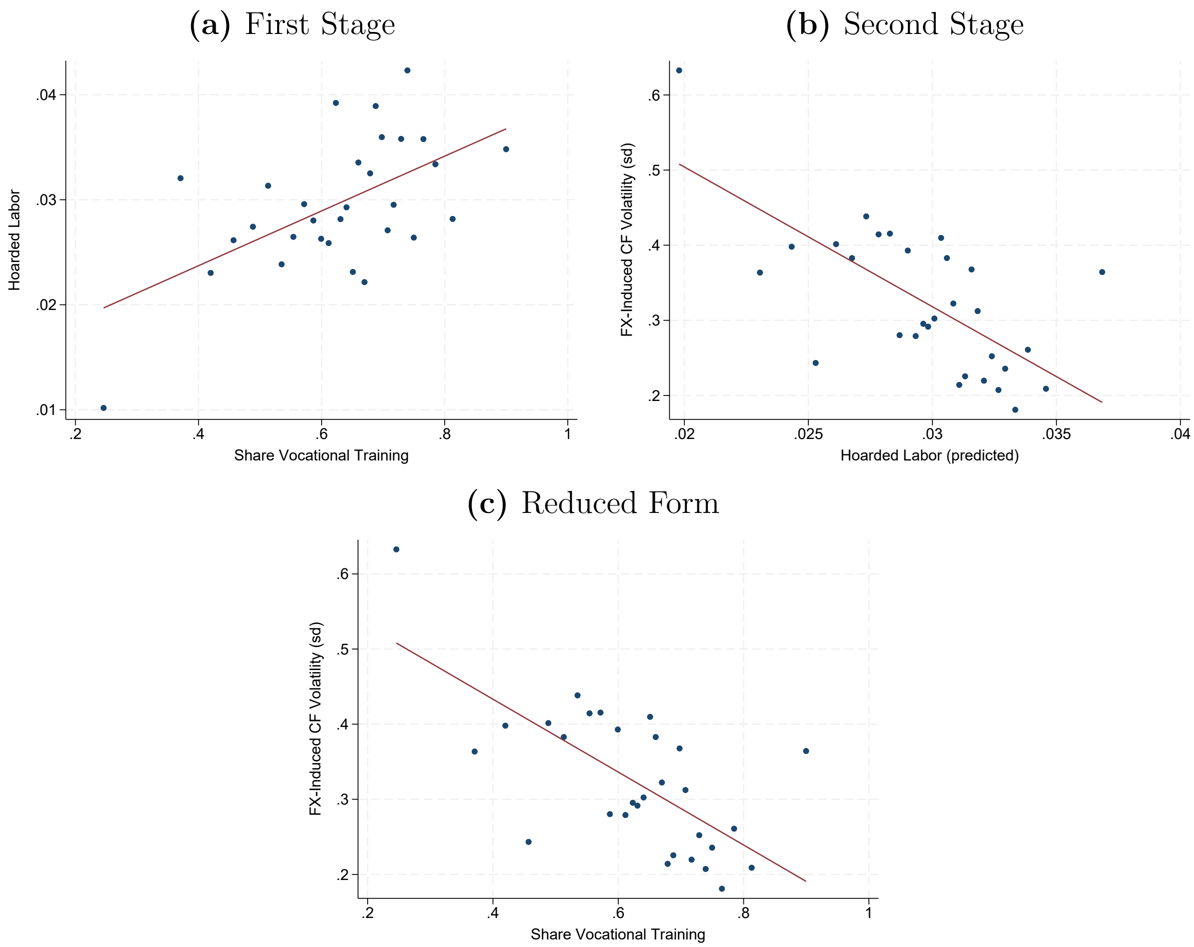
Notes: The figure shows binned scatterplots of total CF volatility in panel (a) and FX-induced CF volatility in panel (b) against hoarded labor. Included controls are size (log assets) and the revenue change 19-20, as well as industry-by-region FEs. The inclusion of controls and fixed effects explains the negative values of hoarded labor. In each case the standard deviation is considered, based on data between 2010 and 2019 scaled by annual revenue. For details on the construction of the measures *FX-induced CF Volatility* and *Hoarded Labor* see sections 5.3 and 4.2. The results are based on firms with FX data (see panel (b) of Table 1).

Figure 10: Relevance of Net FX Gains



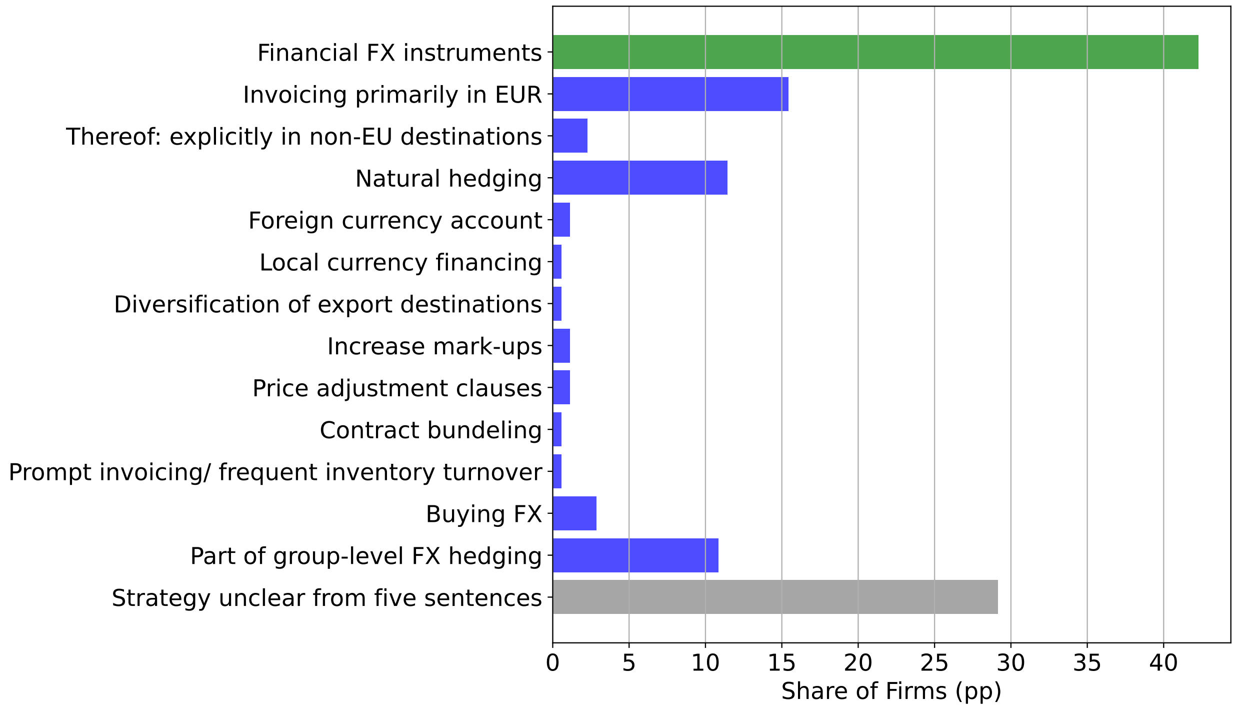
Notes: The figure shows the distribution of net FX gains scaled by EBIT (in pp) in the years 2017-2019. Attention is restricted per year to firms with positive EBIT. The rightmost (leftmost) bins in each panel correspond to firms with net FX gains to EBIT above 10% (below -10%), grouped due to data protection. The results are based on firms with FX data (see panel (b) of Table 1).

Figure 11: Effect of Hoarded Labor on FX-Induced CF Volatility



Notes: The figure shows binned scatterplots of the first stage in panel (a), the second stage in panel (b), and the reduced form in panel (c) of the design (R3). The same set of controls are inluded as in the baseline specification (columns 1 and 2 of panel (b) in Table 5). For details on the construction of the measures *FX-induced CF Volatility* and *Hoarded Labor* see sections 5.3 and 4.2.

Figure 12: 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 C5 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
Equity/Assets (pp)	40.909	40.897	1.759	41.652	84.804	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	43.201	4.002	36.406	43.309	49.571	6913
Avrg Wage (EUR, daily, full-time)	45.712	18.542	22.286	43.097	76.650	6913
Avrg Tenure	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
Equity/Assets (pp)	40.729	31.562	2.226	41.157	83.999	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	42.825	3.507	36.678	43.058	48.375	2352
Avrg Wage (EUR, daily, full-time)	52.789	17.915	31.111	49.954	82.639	2352
Avrg Tenure	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
CF Volatility (sd)	4.472	10.036	0.252	2.094	13.233	2352
FX-Induced CF Volatility (sd net gains)	0.323	0.615	0.002	0.117	1.309	2352
FX-Induced CF Volatility (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
Financial Hedging 2019	0.265	0.441	0.000	0.000	1.000	2352
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 4.2, details on *FX-Induced CF Volatility* see section 5.2 and details on *Financial Hedging* and *Active FX Management w/ AI* see Appendices C4 and C5.

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 $\times$ 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 4.2. 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: Difference between Total and FX-Induced CF Volatility

(a) Total vs. FX-Induced CF Volatility

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

(b) FX-Induced CF Volatility

	Dep. Variable: FX-Induced CF Volatility							
	OLS		OLS		OLS		OLS	
	sd	max	sd	max	sd	max	sd	max
Hoarded Labor	-0.451**	-0.766**	-0.708***	-1.187***	-0.711***	-1.271***	-0.519**	-0.893**
	(0.20)	(0.37)	(0.22)	(0.32)	(0.26)	(0.39)	(0.21)	(0.39)
Log Assets	0.065***	0.099***	0.070***	0.102***	0.070***	0.102***	0.064***	0.097***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)
Export Share	0.456***	0.691***	0.478***	0.743***	0.478***	0.743***	0.458***	0.695***
	(0.06)	(0.10)	(0.08)	(0.13)	(0.08)	(0.13)	(0.06)	(0.10)
Revenue Change 19-20	-0.039	-0.038			-0.005	-0.119	-0.047	-0.053
	(0.16)	(0.26)			(0.21)	(0.32)	(0.16)	(0.26)
Value Added per Employee			0.014	-0.004	0.014	-0.004		
			(0.01)	(0.01)	(0.01)	(0.01)		
ROA (pp)							-0.002*	-0.003*
							(0.00)	(0.00)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.112	0.092	0.117	0.099	0.117	0.099	0.113	0.094
Adj. R^2	0.082	0.061	0.080	0.061	0.079	0.060	0.082	0.062
N Firms	2,319	2,319	1,640	1,640	1,640	1,640	2,319	2,319

Notes: The table reports estimated OLS coefficients from specification (R2). Columns 1-5 of panel (a) use total CF volatility on the LHS, while column 6 of panel (a) and panel (b) 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 5.3 for details). Column 1 of panel (a) 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*. For details on the construction of *Hoarded Labor* see section 4.2. 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 4: Heterogeneity by Firm Characteristics

	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 5.3 for details). For details on the construction of *Hoarded Labor* see section 4.2. 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 5: Impact of Hoarded Labor on FX-Induced CF Volatility

(a) OLS vs. 2SLS

	Dep. Variable: FX-Induced CF Volatility					
	OLS		2SLS		Reduced Form	
	sd	max	sd	max	sd	max
Hoarded Labor	-0.451**	-0.766**	-18.432***	-29.022***		
	(0.20)	(0.37)	(6.41)	(9.73)		
Log Assets	0.065***	0.099***	-0.027	-0.045	0.062***	0.095***
	(0.02)	(0.02)	(0.04)	(0.06)	(0.02)	(0.02)
Export Share	0.456***	0.691***	0.606***	0.927***	0.407***	0.613***
	(0.06)	(0.10)	(0.10)	(0.17)	(0.06)	(0.09)
Revenue Change 19-20	-0.039	-0.038	-3.423***	-5.356***	0.013	0.055
	(0.16)	(0.26)	(1.21)	(1.85)	(0.14)	(0.23)
Share Vocational Training					-0.485***	-0.764***
					(0.12)	(0.18)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Instrument 1st Stage			.026	.026		
Partial R^2 1st Stage			.005	.005		
Kleibergen-Paap F-statistic			15.150	15.150		
Anderson-Rubin χ^2 p-value			0.000	0.000		
N Firms	2,319	2,319	2,319	2,319	2,319	2,319

(b) 2SLS Robustness

	Dep. Variable: FX-Induced CF Volatility					
	2SLS		2SLS		2SLS	
	sd	max	sd	max	sd	max
Hoarded Labor	-13.772***	-24.557***	-15.216***	-27.190***	-20.139***	-31.761***
	(4.90)	(7.67)	(5.54)	(8.69)	(7.24)	(11.00)
Log Assets	0.003	-0.018	-0.001	-0.026	-0.043	-0.070
	(0.04)	(0.05)	(0.04)	(0.06)	(0.04)	(0.07)
Export Share	0.708***	1.155***	0.679***	1.101***	0.634***	0.972***
	(0.13)	(0.22)	(0.13)	(0.22)	(0.11)	(0.18)
Revenue Change 19-20			-3.037***	-5.537***	-3.701***	-5.802***
			(1.15)	(1.83)	(1.35)	(2.07)
Value Added per Employee	0.007	-0.015	0.000	-0.028**		
	(0.01)	(0.01)	(0.01)	(0.01)		
ROA (pp)					-0.013***	-0.021***
					(0.00)	(0.01)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Instrument 1st Stage	.04	.04	.036	.036	.024	.024
Partial R^2 1st Stage	.011	.011	.022	.022	.004	.004
Kleibergen-Paap F-statistic	19.601	19.601	17.714	17.714	13.203	13.203
Anderson-Rubin χ^2 p-value	0.001	0.000	0.001	0.000	0.000	0.000
N Firms	1,640	1,640	1,640	1,640	2,319	2,319

Notes: The table reports the estimated coefficients from specification (R3) instrumenting *Hoarded Labor* with *Share Vocational Training*, the share of employees with vocational training. Panel (a) shows the OLS, 2SLS and reduced-form estimates, panel (b) shows 2SLS estimates for different sets of control variables. 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 5.3 for details). For details on the construction of *Hoarded Labor* see section 4.2. 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: Alternative Instrument: Share of Employees in Shortage Occuaptions

	Dep. Variable: FX-Induced CF Volatility					
	2SLS		2SLS		2SLS	
	sd	max	sd	max	sd	max
Hoarded Labor	-6.071*	-10.827**	-5.650*	-9.411**	-7.518*	-12.692*
	(3.18)	(5.22)	(2.99)	(4.60)	(4.30)	(6.75)
Log Assets	0.036	0.047	0.045*	0.060	0.037	0.045
	(0.02)	(0.04)	(0.03)	(0.04)	(0.03)	(0.05)
Export Share	0.503***	0.775***	0.565***	0.888***	0.572***	0.901***
	(0.07)	(0.11)	(0.10)	(0.15)	(0.10)	(0.16)
Revenue Change 19-20	-1.097*	-1.932*			-1.428	-2.507*
	(0.61)	(1.03)			(0.91)	(1.45)
Value Added per Employee			0.011	-0.008	0.007	-0.015*
			(0.01)	(0.01)	(0.01)	(0.01)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Instrument 1st Stage	.026	.026	.035	.035	.025	.025
Partial R^2 1st Stage	.005	.005	.008	.008	.018	.018
Kleibergen-Paap F-statistic	12.290	12.290	14.026	14.026	8.877	8.877
Anderson-Rubin χ^2 p-value	0.024	0.012	0.033	0.018	0.037	0.021
N Firms	2,319	2,319	1,640	1,640	1,640	1,640

Notes: The table reports the estimated coefficients from a specification analogous to (R3) now instrumenting *Hoarded Labor* with *Shortage Share*, the share of employees in shortage occupations as of the end of 2019 (see section 6.3 for details). 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 5.3 for details). For details on the construction of *Hoarded Labor* see section 4.2. 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 7: Propensity to Use FX Derivatives as Outcome

	Dep. Variable: Derivatives Usage				
	Logit			OLS	2SLS
	(1)	(2)	(3)	(4)	(5)
Hoarded Labor	1.628*	1.712*	1.611	0.278	1.022
	(0.98)	(0.99)	(1.01)	(0.19)	(2.38)
Log Assets	0.469***	0.489***	0.502***	0.091***	0.095***
	(0.04)	(0.04)	(0.04)	(0.01)	(0.01)
Export Share	1.014***	1.010***	1.035***	0.182***	0.176***
	(0.18)	(0.19)	(0.20)	(0.04)	(0.04)
Revenue Change 19-20	1.512***	1.647***	1.686***	0.279***	0.419
	(0.54)	(0.55)	(0.57)	(0.10)	(0.46)
Industry FEs	No	Yes	No	No	No
Region FEs	No	Yes	No	No	No
Industry x Region FEs	No	No	Yes	Yes	Yes
Instrument 1st Stage					.026
Kleibergen-Paap F-statistic					14.974
N Firms	2,352	2,344	2,254	2,319	2,319

Notes: The table reports logit (columns 1-3), OLS (column 4) and 2SLS (column 5) estimates using a binary variable whether the firm uses FX derivatives in 2019 as outcome (for details see Appendix C4). In the 2SLS, *Hoarded Labor* is instrumented with *Share Vocational Training*. *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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Heterogeneity by Active FX Management

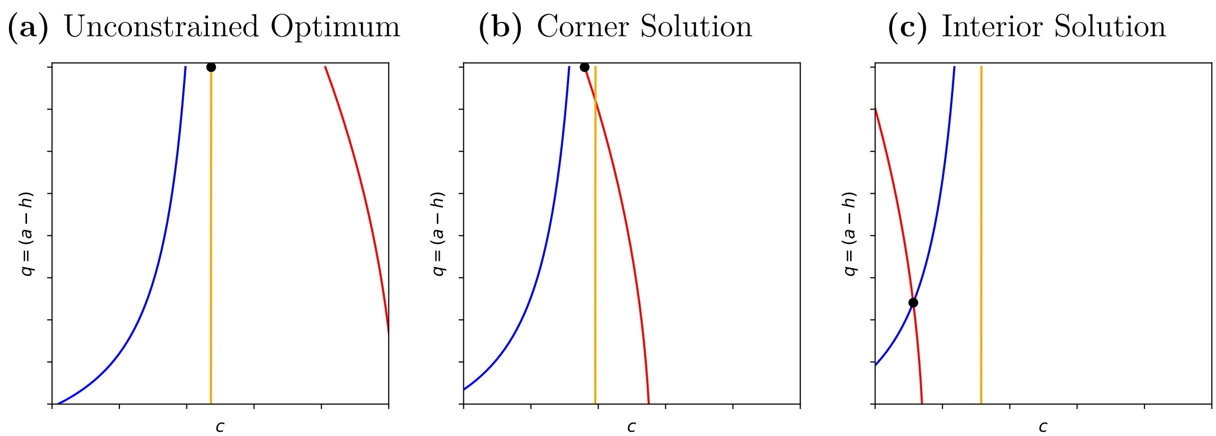
	Dep. Variable: FX-Induced CF Volatility			
	OLS		2SLS	
	sd	max	sd	max
Hoarded Labor	-0.327	-0.661*	-11.390*	-17.346*
	(0.24)	(0.38)	(6.43)	(9.43)
Active FX Management × Hoarded Labor	-0.234	-0.166	-14.288*	-23.538*
	(0.36)	(0.65)	(8.55)	(13.40)
Active FX Management	0.093***	0.152***	0.537**	0.888**
	(0.03)	(0.05)	(0.27)	(0.42)
Log Assets	0.061***	0.092***	-0.017	-0.028
	(0.02)	(0.02)	(0.04)	(0.06)
Export Share	0.426***	0.640***	0.501***	0.753***
	(0.06)	(0.10)	(0.11)	(0.17)
Revenue Change 19-20	-0.052	-0.063	-3.109***	-4.826***
	(0.16)	(0.26)	(1.18)	(1.79)
Industry x Region FEs	Yes	Yes	Yes	Yes
F main effect			7.572	7.572
F interaction			5.004	5.004
Kleibergen-Paap F-statistic			7.513	7.513
N Firms	2,316	2,316	2,316	2,316

Notes: This table reports OLS and 2SLS estimates from a specification analogous to (R3) allowing for heterogeneity of the effect depending on whether the firm actively manages FX risk in which case *Active FX Management* takes the value of 1. For details on the variable *Active FX Management* see Appendix C5. 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 5.3 for details). For details on the construction of *Hoarded Labor* see section 4.2. Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

APPENDIX

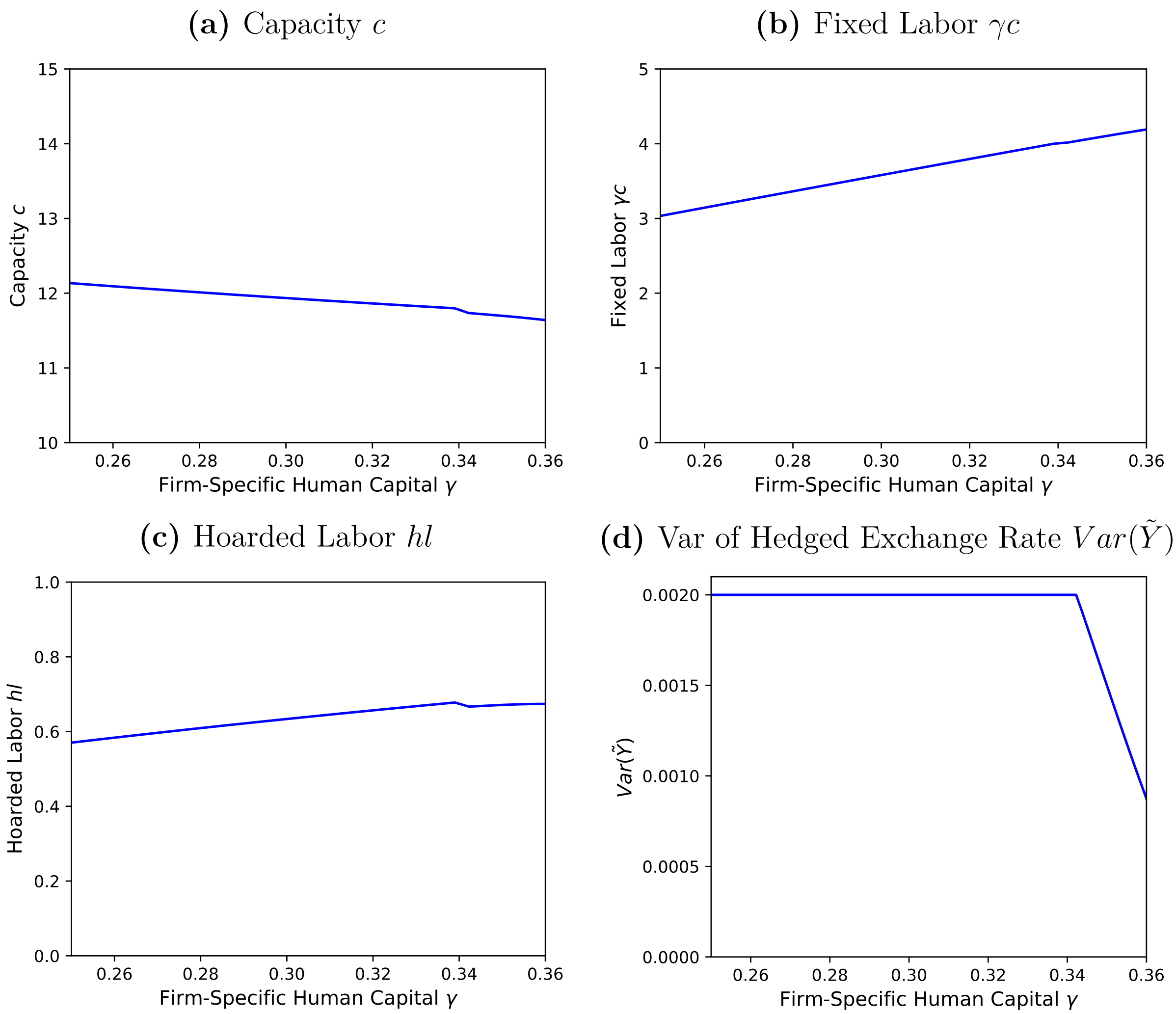
A Appendix: Additional Figures and Tables

Figure A.1: Illustration of the Model Solution for Increasing Levels of γ



Notes: This figure illustrates 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.

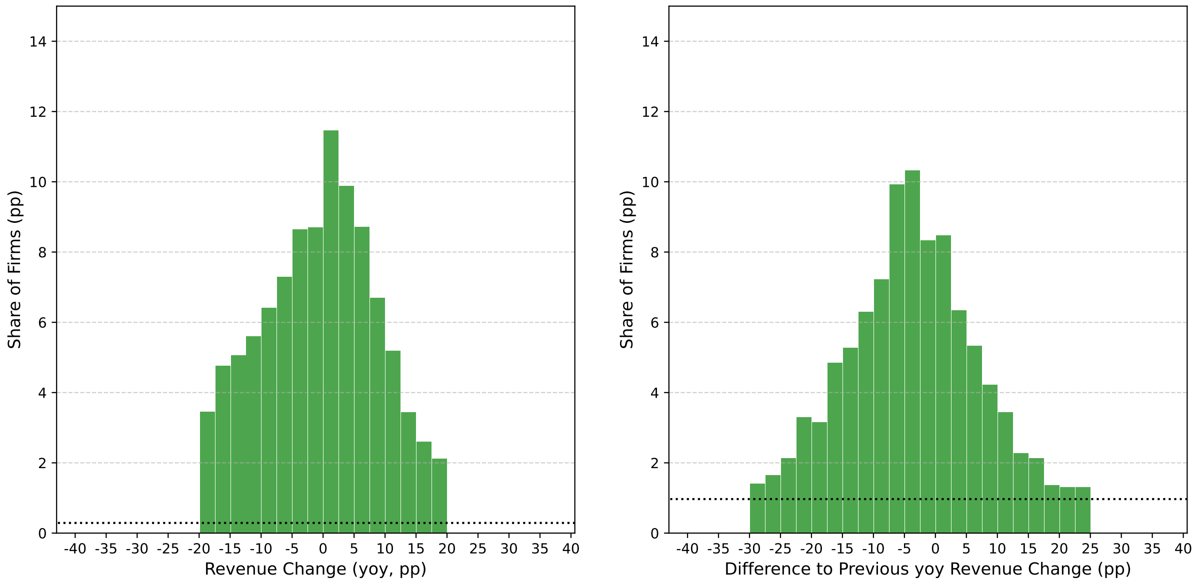
Figure A.2: Model: Solution with Alternative Constraint



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 A.3: Revenue Distribution

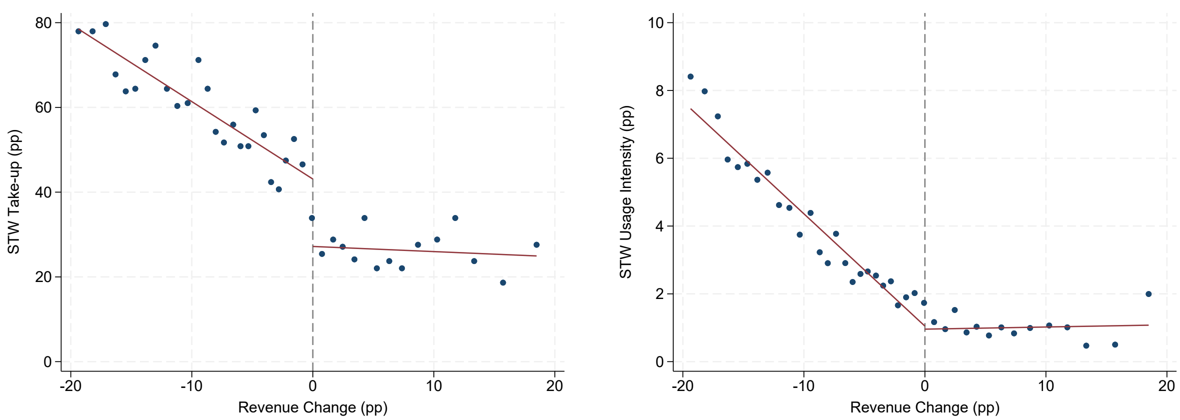
(a) Revenue Change 2020 **(b)** Difference to Previous Revenue Change



Notes: The figure shows the year-on-year revenue change in 2020 (in pp) in panel (a) and the difference in the year-on-year revenue change between 2020 and 2019 (in pp) in panel (b). The results are based on the full sample of firms (see panel (a) of Table 1). No information below the dotted line is available due to data protection (less than 20 establishments).

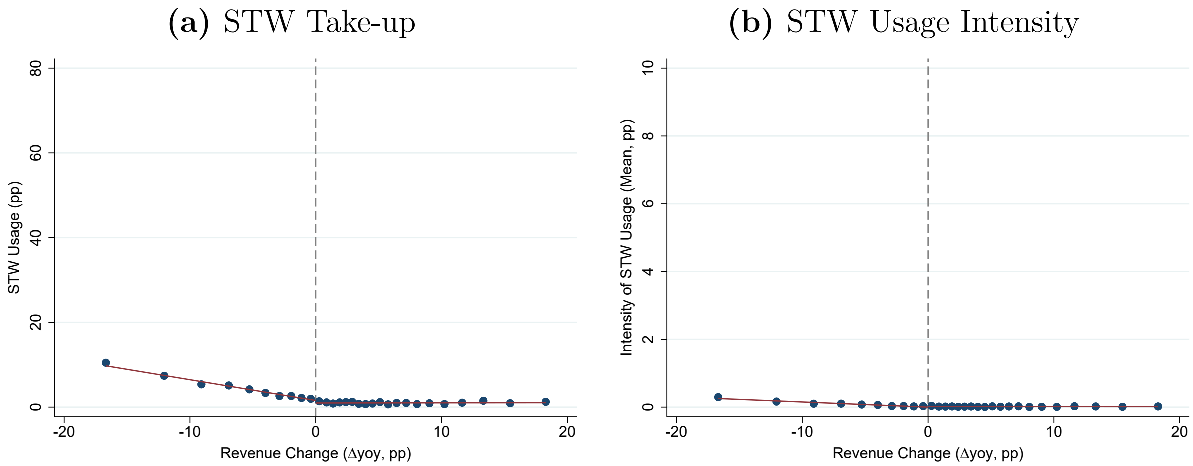
Figure A.4: STW Usage by Firm-Level Revenue Change for Firms With FX Data

(a) STW Take-up **(b)** STW Usage Intensity



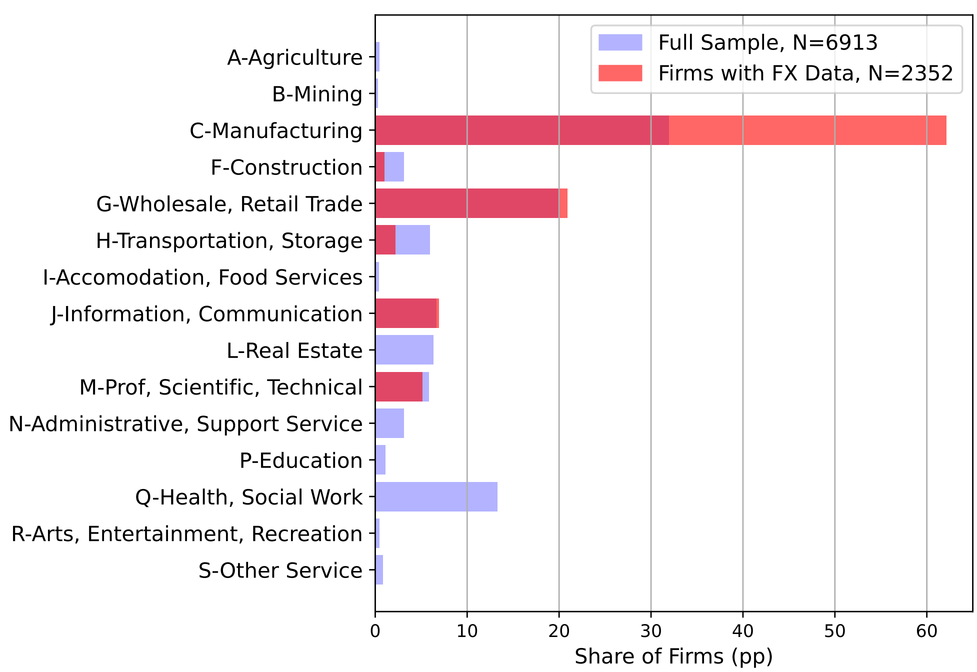
Notes: The figure shows binned scatterplots of STW take-up in panel (a) and of the STW usage intensity in panel (b) against the year-on-year revenue change 2020 (in pp). The results are based on firms with FX data (see panel (b) of Table 1). The time window considered for STW take-up (binary) and STW usage intensity is June until December 2020. STW usage intensity is defined as the average monthly worker-equivalent of reduced hours relative to employment (for details see section 4.2).

Figure A.5: Placebo 2012-2019: STW Usage by Firm-Level Revenue Change



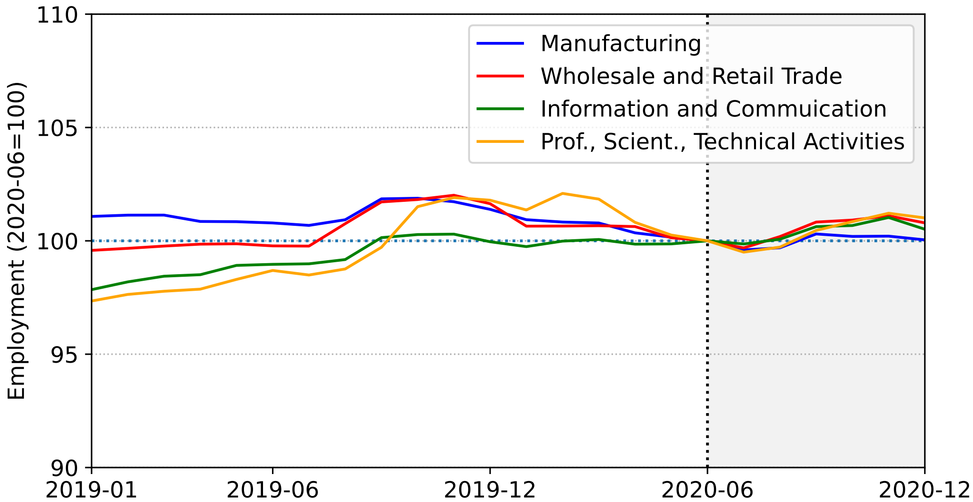
Notes: The figure shows binned scatterplots of STW take-up in panel (a) and of the STW usage intensity in panel (b) against the annual year-on-year change in revenue (in pp). The sample consists of pooled firm-year observations for the years 2012-2019. The annual *Intensity of STW Usage* in a given year is defined analogously to before (cf. section 4.2) based on all months per year.

Figure A.6: Industry Composition Full Sample vs. Firms with FX Data



Notes: The 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).

Figure A.7: 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 4.2 for details). Employment in June 2020 is normalized to 100.

Table A.1: Who Hoards? Firm Charactistics

(a) Full Sample

	Dep. Variable: Labor Hoarding					
	(1)	(2)	(3)	(4)	(5)	(6)
Revenue Change 19-20	-1.696***	-1.699***	-1.788***	-1.801***	-1.693***	-1.963***
	(0.14)	(0.14)	(0.17)	(0.17)	(0.14)	(0.18)
Revenue Change 19-20 × Revenue Growth	1.265***	1.292***	1.311***	1.636***	1.253***	1.650***
	(0.20)	(0.20)	(0.23)	(0.23)	(0.20)	(0.29)
Revenue Growth	-0.119***	-0.122***	-0.117***	-0.122***	-0.119***	-0.139***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Log Assets	-0.002					
	(0.00)					
Age		0.000*				
		(0.00)				
Value Added per Employee			-0.019***			
			(0.01)			
Revenue Growth Prev Years				0.008		
				(0.05)		
Equity/Assets					-0.037***	
					(0.01)	
Export Share						-0.042
						(0.03)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
N Firms	6,891	6,862	5,082	5,154	6,891	3,250
R^2	0.243	0.244	0.263	0.250	0.244	0.191
Adj. R^2	0.221	0.222	0.235	0.223	0.222	0.166

(b) Firms with FX Data

	Dep. Variable: Labor Hoarding					
	(1)	(2)	(3)	(4)	(5)	(6)
Revenue Change 19-20	-1.794***	-1.815***	-1.909***	-1.911***	-1.797***	-1.812***
	(0.22)	(0.22)	(0.26)	(0.23)	(0.21)	(0.22)
Revenue Change 19-20 × Revenue Growth	1.721***	1.854***	1.816***	2.179***	1.717***	1.748***
	(0.37)	(0.37)	(0.44)	(0.40)	(0.36)	(0.37)
Revenue Growth	-0.149***	-0.155***	-0.118***	-0.157***	-0.148***	-0.150***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Log Assets	-0.011					
	(0.01)					
Age		0.001**				
		(0.00)				
Value Added per Employee			-0.019***			
			(0.00)			
Revenue Growth Prev Years				0.022		
				(0.06)		
Equity/Assets					-0.066	
					(0.04)	
Export Share						-0.053
						(0.04)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
N Firms	2,319	2,308	1,640	1,964	2,319	2,319
R^2	0.180	0.182	0.186	0.178	0.181	0.180
Adj. R^2	0.152	0.155	0.151	0.147	0.153	0.152

Notes: The table shows the estimated OLS coefficients from a regression of *Labor Hoarding* on the revenue change and firm characteristics for the full sample in panel (a) and for firms with FX data in panel (b). *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 4.2. I allow discontinuity of the correlation with revenue change depending on whether the firm experienced positive revenue growth or not in 2020. Firm characteristics are as of 2019 (or available information in Dafne as of May 2022 for *Export Share*). *Revenue Growth Prev Years* is the constant average growth rate of revenue between 2015 and 2019.

Table A.2: Who Hoards? Workforce Characteristics

(a) Full Sample

	Dep. Variable: Labor Hoarding							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Revenue Change 19-20	-1.692***	-1.707***	-1.702***	-1.706***	-1.695***	-1.694***	-1.687***	-1.683***
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Revenue Change 19-20 × Revenue Growth	1.196***	1.294***	1.251***	1.284***	1.279***	1.283***	1.243***	1.251***
	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)
Revenue Growth	-0.120***	-0.121***	-0.119***	-0.121***	-0.121***	-0.122***	-0.120***	-0.119***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Avrg Age	-0.009***							
	(0.00)							
Avrg Wage		-0.003***						
		(0.00)						
Avrg Tenure			-0.003**					
			(0.00)					
Share w/ Temporary Contracts				0.149***				
				(0.04)				
Share w/ Vocational Training					0.074**			
					(0.03)			
Share w/ College Education						-0.148***		
						(0.03)		
Occupation-Based: Shortage Share							0.073**	
							(0.03)	
Occupation-Based: Tenure								0.176
								(0.11)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N Firms	6,891	6,891	6,891	6,891	6,891	6,891	6,891	6,891
R^2	0.249	0.252	0.244	0.245	0.244	0.246	0.244	0.243
Adj. R^2	0.227	0.230	0.222	0.223	0.222	0.224	0.222	0.221

(b) Firms with FX Data

	Dep. Variable: Labor Hoarding							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Revenue Change 19-20	-1.797***	-1.798***	-1.782***	-1.797***	-1.783***	-1.776***	-1.769***	-1.744***
	(0.22)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.22)	(0.22)
Revenue Change 19-20 × Revenue Growth	1.726***	1.684***	1.759***	1.734***	1.742***	1.742***	1.676***	1.710***
	(0.37)	(0.37)	(0.36)	(0.37)	(0.36)	(0.36)	(0.37)	(0.37)
Revenue Growth	-0.151***	-0.148***	-0.149***	-0.151***	-0.151***	-0.152***	-0.147***	-0.151***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Avrg Age	-0.002							
	(0.00)							
Avrg Wage		-0.004***						
		(0.00)						
Avrg Tenure			0.007***					
			(0.00)					
Share w/ Temporary Contracts				0.069				
				(0.08)				
Share w/ Vocational Training					0.253***			
					(0.07)			
Share w/ College Education						-0.257***		
						(0.06)		
Occupation-Based: Shortage Share							0.179**	
							(0.07)	
Occupation-Based: Tenure								0.730***
								(0.27)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N Firms	2,319	2,319	2,319	2,319	2,319	2,319	2,319	2,319
R^2	0.180	0.193	0.182	0.180	0.185	0.186	0.182	0.182
Adj. R^2	0.152	0.166	0.154	0.152	0.157	0.158	0.154	0.154

Notes: The table shows the estimated OLS coefficients from a regression of *Labor Hoarding* on the revenue change and workforce characteristics for the full sample in panel (a) and for firms with FX data in panel (b). *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 4.2. I allow discontinuity of the correlation with revenue change depending on whether the firm experienced positive revenue growth or not in 2020. Workforce characteristics are as of 2019. For details on *Occupation-Based: Shortage Share* and *Occupation-Based: Tenure* see sections 6.3 and 6.1.

Table A.3: Robustness: Comovement of Changes in Profitability with Industry-Wide Order Changes by Labor Hoarding

	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

Notes: The table 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 4.2. 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). 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 A.4: Summary Statistics for the Analyses in Table 2 and Table A.3

	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: The table provides summary statistics for the panel analyses in Table 2 (top) and Table A.3 (bottom). 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 A.5: Summary Statistics for Firms With a High/ Low Vocational Share

	Low Vocational Share					High Vocational Share					t-test Means
	Mean	p10	p50	p90	N	Mean	p10	p50	p90	N	
Core Financial Information (2019)											
Assets (mil EUR)	354.58	14.12	46.59	343.56	1176	256.93	14.33	45.49	206.08	1176	0.57
Revenue (mil EUR)	260.58	21.23	72.08	375.21	1176	212.92	24.13	74.47	279.14	1176	0.53
Employees	431.23	41.00	189.50	752.00	1176	470.24	67.00	250.00	709.00	1176	0.71
Equity/Assets (pp)	38.73	7.10	38.79	76.09	1176	42.73	9.70	42.97	77.28	1176	0.00
Cash/Assets (pp)	11.35	0.06	5.21	31.54	1176	7.72	0.02	3.28	21.75	1176	0.00
ROA (pp)	8.38	-4.11	6.68	24.06	1176	6.52	-5.16	5.64	19.34	1176	0.00
Value Added per Employee (mil EUR)	0.24	0.06	0.11	0.25	837	0.09	0.05	0.08	0.14	824	0.05
Information on Exports and FX-Volatility											
Export Share	0.45	0.05	0.46	0.85	1176	0.43	0.08	0.42	0.79	1176	0.14
1(Export Outside Europe)	0.83	0.00	1.00	1.00	555	0.81	0.00	1.00	1.00	637	0.39

Notes: The table reports firm-level summary statistics separately for firms with a high (above-median) and low (below-median) vocational share, that is, share of emplyoees with vocational training. See section 6.1 for details.

Table A.6: Vocational Share and Other Firm Characteristics

	Vocational Share			
	(1)	(2)	(3)	(4)
ROA (pp)	-0.000			
	(0.00)			
Cash/Assets		-0.114***		
		(0.03)		
Value Added per Employee			-0.008***	
			(0.00)	
1(Exports to Outside Europe)				-0.002
				(0.01)
Industry x Region FEs	Yes	Yes	Yes	Yes
R^2	0.433	0.438	0.443	0.360
Adj. R^2	0.414	0.419	0.420	0.331
N Firms	2,319	2,319	1,640	1,163

Notes: The table shows the estimated coefficients of a cross-sectional regression of the firm-level vocational share, that is, the share of emplyoees with vocational training, on various other firm characteristics. Variables are defined as of 2019. Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Vocational Share and the Export Share

	Vocational Share		
	(1)	(2)	(3)
Export Share	0.000**	-0.001	0.000
	(0.00)	(0.00)	(0.00)
Firm FEs	Yes	No	Yes
Year FEs	No	Yes	Yes
R^2	0.965	0.003	0.967
Adj. R^2	0.959	0.002	0.962
N Observations	10,991	10,991	10,991
N Firms	1,678	1,678	1,678

Notes: The table shows the estimated coefficients from a panel regression of the firm-level vocational share, that is, the share of emplyoees with vocational training, on export share, defined as foreign revenue to revenue. The regression is based on the subset of the firms with FX data for which panel information is available between 2010 and 2019. Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Robustness

(a) Measure of Hoarded Labor Based on the Eased-Access Episode in 2009

	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

(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	-8.218	-19.703*		
	(0.28)	(0.48)	(6.25)	(11.09)		
Log Assets	0.055**	0.090***	0.020	0.004	0.055**	0.089***
	(0.02)	(0.03)	(0.04)	(0.07)	(0.02)	(0.03)
Export Share	0.539***	0.745***	0.622***	0.952***	0.497***	0.652***
	(0.10)	(0.16)	(0.14)	(0.25)	(0.09)	(0.15)
Revenue Change 19-20	0.083	0.567	-1.475	-3.281	0.154	0.624*
	(0.22)	(0.38)	(1.26)	(2.29)	(0.19)	(0.36)
Share Vocational Training					-0.335	-0.804**
					(0.23)	(0.36)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Instrument 1st Stage			.041	.041		
Partial R^2 1st Stage			.007	.007		
Kleibergen-Paap F-statistic			8.224	8.224		
Anderson-Rubin χ^2 p-value			0.141	0.022		
N Firms	957	957	957	957	957	957

Notes: The table reports robustness checks for specifications (R3). In panel (a) *Hoarded Labor* is constructed based on STW usage during the eased-access episode in 2009 (see section 4.2 for details). Control variables as well as *Vocational Share* are as of 2008. 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 5.3 for details). Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: Summary Statistics for Firms With a High/ Low Shortage Share

	Low Shortage Share					High Shortage Share					t-test Means
	Mean	p10	p50	p90	N	Mean	p10	p50	p90	N	
Core Financial Information (2019)											
Assets (mil EUR)	265.80	13.73	44.99	253.40	1176	345.71	14.62	47.08	276.55	1176	0.64
Revenue (mil EUR)	217.29	23.09	78.21	333.95	1176	256.20	21.54	68.36	332.99	1176	0.61
Employees	323.50	37.00	172.00	605.00	1176	577.97	87.00	277.00	866.00	1176	0.01
Equity/Assets (pp)	40.52	6.63	41.15	76.33	1176	40.94	9.72	41.17	77.02	1176	0.75
Cash/Assets (pp)	9.07	0.02	3.73	25.51	1176	9.99	0.04	4.70	27.64	1176	0.09
ROA (pp)	7.75	-3.66	6.11	22.31	1176	7.14	-5.78	6.18	21.14	1176	0.28
Value Added per Employee (mil EUR)	0.24	0.05	0.10	0.25	818	0.10	0.06	0.09	0.15	843	0.06
Information on Exports and FX-Volatility											
Export Share	0.42	0.06	0.40	0.80	1176	0.47	0.07	0.48	0.82	1176	0.00
1(Export Outside Europe)	0.76	0.00	1.00	1.00	557	0.87	0.00	1.00	1.00	635	0.00

Notes: The table reports firm-level summary statistics separately for firms with a high (above-median) and low (below-median) shortage share, that is, share of employees in shortage occupations (see section 6.3 for details).

Table A.10: Shortage Share and Other Firm Characteristics

	Shortage Share			
	(1)	(2)	(3)	(4)
ROA (pp)	-0.000			
	(0.00)			
Cash/Assets		0.033		
		(0.02)		
Value Added per Employee			-0.005***	
			(0.00)	
1(Exports to Outside Europe)				0.014
				(0.01)
Industry x Region FEs	Yes	Yes	Yes	Yes
R^2	0.182	0.182	0.193	0.191
Adj. R^2	0.156	0.156	0.160	0.155
N Firms	2,319	2,319	1,640	1,163

Notes: The table shows the estimated coefficients from a cross-sectional regression of the firm-level shortage share, that is, the share of employees in shortage occupations, on various other firm characteristics. Variables are defined as of 2019. Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11: Alternative Instrument: Tenure-Based Measure for Firm-Specific Human Capital

	Dep. Variable: FX-Induced CF Volatility							
	2SLS		2SLS		2SLS		2SLS	
	sd	max	sd	max	sd	max	sd	max
Hoarded Labor	-2.834	-13.758	-2.260	-12.405*	-3.801	-23.894	-4.369	-19.292
	(7.91)	(12.19)	(5.20)	(7.06)	(10.12)	(18.14)	(10.59)	(18.41)
Log Assets	0.053	0.032	0.062**	0.044	0.055	-0.010	0.043	-0.003
	(0.04)	(0.06)	(0.03)	(0.04)	(0.05)	(0.09)	(0.06)	(0.10)
Export Share	0.476***	0.799***	0.505***	0.938***	0.520***	1.050***	0.493***	0.858***
	(0.08)	(0.13)	(0.11)	(0.17)	(0.15)	(0.29)	(0.10)	(0.19)
Revenue Change 19-20	-0.487	-2.483			-0.650	-4.848	-0.764	-3.480
	(1.49)	(2.31)			(2.11)	(3.80)	(1.98)	(3.44)
Value Added per Employee			0.013	-0.009	0.011	-0.025		
			(0.01)	(0.01)	(0.02)	(0.02)		
ROA (pp)							-0.004	-0.014
							(0.01)	(0.01)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Instrument 1st Stage	.057	.057	.115	.115	.059	.059	.044	.044
Partial R^2 1st Stage	.001	.001	.006	.006	.014	.014	.001	.001
Kleibergen-Paap F-statistic	3.651	3.651	9.482	9.482	2.733	2.733	2.125	2.125
Anderson-Rubin χ^2 p-value	0.718	0.164	0.663	0.039	0.708	0.041	0.675	0.139
N Firms	2,319	2,319	1,640	1,640	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 a tenure-based measure. For firm i, the tenure-based measure is calculated as the share of employees per occupation weighted by an occupation-speficic tenure measure, that is, the average share of employees per occupation who have been with their employer for more than 10 years. 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 5.3 for details). For details on the construction of *Hoarded Labor* see section 4.2. 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 A.12: Heterogeneity by Cash Holdings

	Dep. Variable: FX-Induced CF Volatility			
	OLS		2SLS	
	sd	max	sd	max
Hoarded Labor	-0.604**	-1.081**	-19.333**	-30.502**
	(0.30)	(0.45)	(7.83)	(11.91)
Cash Holdings below p50 × Hoarded Labor	0.309	0.593	1.509	1.961
	(0.35)	(0.59)	(7.71)	(12.12)
Cash Holdings below p50	-0.062**	-0.062	-0.031	0.004
	(0.03)	(0.05)	(0.25)	(0.38)
Log Assets	0.067***	0.101***	-0.028	-0.050
	(0.02)	(0.02)	(0.04)	(0.06)
Export Share	0.448***	0.685***	0.607***	0.937***
	(0.06)	(0.10)	(0.11)	(0.17)
Revenue Change 19-20	-0.044	-0.047	-3.455***	-5.453***
	(0.16)	(0.26)	(1.25)	(1.92)
Industry x Region FEs	Yes	Yes	Yes	Yes
F main effect			7.142	7.142
F interaction			4.287	4.287
Kleibergen-Paap F-statistic			7.364	7.364
N Firms	2,319	2,319	2,319	2,319

Notes: This table reports OLS and 2SLS estimates from a specification analogous to (R3) allowing for heterogeneity in cash holdings (cash-to-assets ratio). 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 5.3 for details). For details on the construction of *Hoarded Labor* see section 4.2. Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.13: Multiple Instruments

	Dep. Variable: FX-Induced CF Volatility							
	2SLS		2SLS		2SLS		2SLS	
	sd	max	sd	max	sd	max	sd	max
Hoarded Labor	-12.225***	-19.894***	-10.248***	-17.976***	-12.662***	-22.367***	-13.105***	-21.376***
	(3.45)	(5.52)	(3.04)	(4.82)	(3.88)	(6.21)	(3.78)	(6.06)
Log Assets	0.005	0.001	0.021	0.016	0.011	-0.003	-0.004	-0.014
	(0.02)	(0.04)	(0.03)	(0.04)	(0.03)	(0.05)	(0.03)	(0.04)
Export Share	0.553***	0.849***	0.645***	1.036***	0.641***	1.029***	0.570***	0.877***
	(0.08)	(0.13)	(0.11)	(0.18)	(0.11)	(0.19)	(0.08)	(0.14)
Revenue Change 19-20	-2.255***	-3.638***			-2.502***	-4.529***	-2.392***	-3.868***
	(0.66)	(1.07)			(0.81)	(1.32)	(0.71)	(1.16)
Value Added per Employee			0.009	-0.012	0.003	-0.024**		
			(0.01)	(0.01)	(0.01)	(0.01)		
ROA (pp)							-0.009***	-0.015***
							(0.00)	(0.00)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	12.982	12.982	16.064	16.064	13.010	13.010	11.621	11.621
Anderson-Rubin χ^2 p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Overidenfication test χ^2 p-value	0.069	0.074	0.150	0.074	0.292	0.200	0.066	0.071
N Firms	2,319	2,319	1,640	1,640	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 *Vocational Share* and *Shortage Share*. For details of the two instruments see sections 6.1 and 6.3. 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 5.3 for details). For details on the construction of *Hoarded Labor* see section 4.2. 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 A.14: Stylized Facts on FX-Derivatives Usage: Summary Statistics

	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

Notes: This table shows summary statistics, separately for derivatives users (as of 2019, RHS) and non-users (LHS). The results are based on firms with FX data (see panel (b) of Table 1). *Export Share* (*Import Share*) is the information availabe from Creditreform (as of May 2022). 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 5.3 for details).

Table A.15: Stylized Facts on FX Derivatives Usage: Relation to FX-Induced CF Volatility

(a) Relevance of Exports

	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

(b) Relevance of Imports

	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

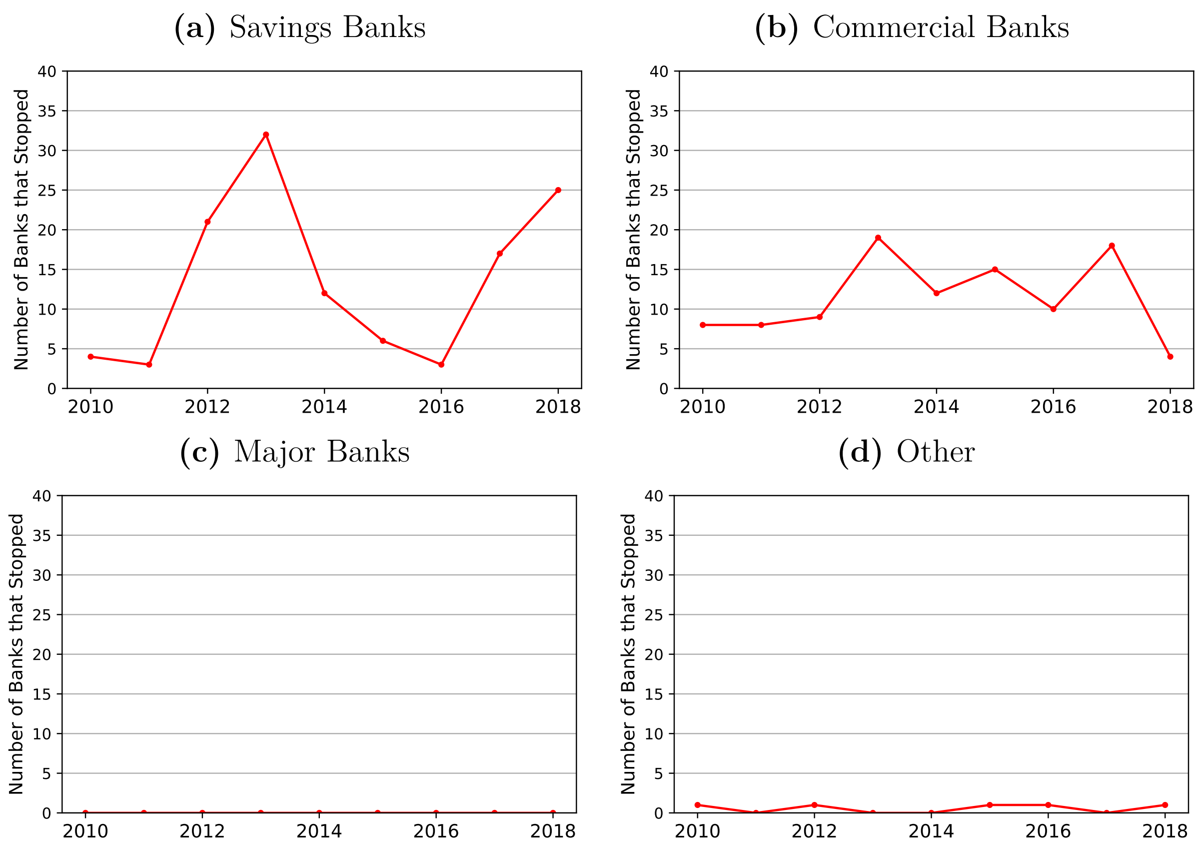
Notes: The table reports estimated OLS coefficients from a regression of *FX-Induced CF Volatility* (*sd*) on the export share in panel (a) and on the import share in panel (b), allowing for heterogeneity between derivatives users and non-users. *Derivatives Usage* is equal to 1 if the firm uses FX derivatives 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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.16: Heterogeneity by a Proxy for Derivatives Service Provision

	Dep. Variable: FX-Induced CF Volatility			
	OLS		2SLS	
	sd	max	sd	max
Hoarded Labor	-0.692***	-0.954**	-16.019**	-22.610*
	(0.24)	(0.42)	(7.84)	(11.71)
1(Local Continued 2014) × Hoarded Labor	0.623*	0.774	-7.722	-16.271
	(0.33)	(0.61)	(15.81)	(25.20)
1(Local Continued 2014)	-0.008	0.016	0.210	0.494
	(0.04)	(0.06)	(0.54)	(0.85)
Log Assets	0.064***	0.098***	-0.020	-0.026
	(0.02)	(0.02)	(0.04)	(0.06)
Export Share	0.443***	0.666***	0.570***	0.845***
	(0.06)	(0.10)	(0.11)	(0.18)
Revenue Change 19-20	-0.001	0.049	-3.494**	-5.257**
	(0.16)	(0.27)	(1.45)	(2.20)
Industry x Region FEs	Yes	Yes	Yes	Yes
Local Bank FEs	Yes	Yes	Yes	Yes
F-statistic main effect			5.94	5.94
F-statistic interaction			2.945	2.945
Kleibergen-Paap F-statistic			3.015	3.015
N Firms	2,193	2,193	2,193	2,193

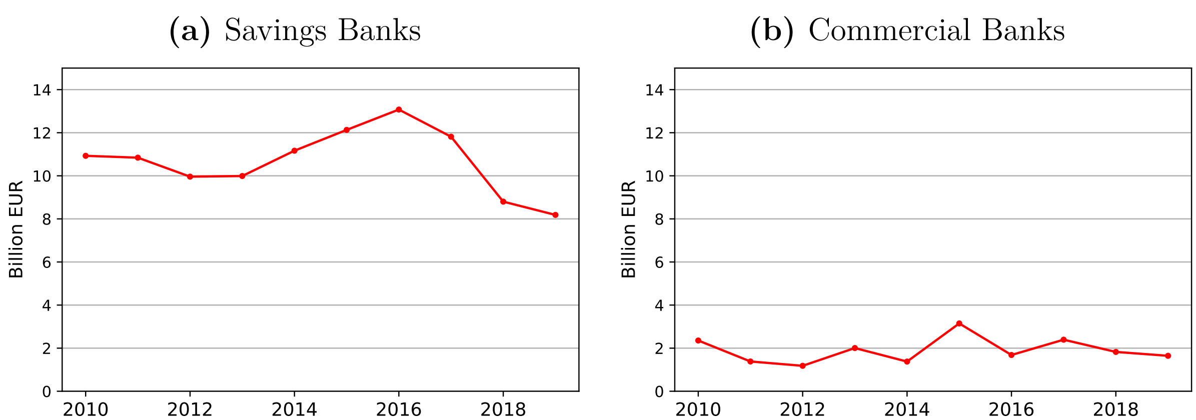
Notes: This table reports OLS and 2SLS estimates from a specification analogous to (R3) allowing for heterogeneity of the effect depending on (proxied) FX-service provision. *1(Local Continued 2014)* takes the value of 1 if a local relationship bank continued offering FX derivatives following the introduction of EMIR (see section 7.1 for details). 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 5.3 for details). For details on the construction of *Hoarded Labor* see section 4.2. Fixed effects based on whether the firm has any banking relationship with a local bank are included. Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.8: Banks that Stopped Selling FX Derivatives by Type of Bank



Notes: The figure shows the number of banks that stopped offering FX derivatives over time per type of bank (Savings Banks (*Sparkassen*), Commercial Banks (*Volksbanken*), major German banks (*Deutsche Bank, Commerzbank, Unicredit*), and other). The depicted year corresponds to the last year a bank reported outstanding FX derivatives on behalf of clients in their annual report (for details on the data construction see Appendix C6).

Figure A.9: Outstanding Amounts of FX Derivatives by Type of Bank



Notes: The figure shows the 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 C6.

B Appendix: Model Proofs

B1 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:

$$f'(x) = -\frac{(x-\mu)}{\sigma^2} f(x). \tag{B2}$$

Hence,

$$\begin{aligned}
E[\min(X,c)] &= \int_{-\infty}^{c} x f(x) dx + \int_{c}^{\infty} c f(x) dx && \text{(B3)}\\
&= -\sigma^2 \int_{-\infty}^{c} -\frac{(x-\mu)}{\sigma^2} f(x) dx + \mu \int_{-\infty}^{c} f(x) dx + \int_{c}^{\infty} c f(x) dx && \text{(B4)}\\
&= -\sigma^2 f(c) + \mu F(c) + c(1 - F(c)), && \text{(B5)}
\end{aligned}$$

and

$$\begin{aligned}
\partial_c E[\min(X,c)] &= -\sigma^2 f'(c) + (\mu - c) f(c) + (1 - F(c)) && \text{(B6)}\\
&= (1 - F(c)). && \text{(B7)}
\end{aligned}$$

With E short-hand for the expected cashflow,

$$E := E[CF_\gamma(c,q)] = E[\min(X,c)]\,[1 - k(a-q) - (1-\gamma)w] - (\gamma w c + b), \tag{B8}$$

it follows that

$$\begin{aligned}
\partial_c E &= [1 - k(a-q) - (1-\gamma)w]\,(1 - F(c)) - \gamma w && \text{(B9)}\\
\partial_c^2 E &= -\,[1 - k(a-q) - (1-\gamma)w]\, f(c) \qquad < 0. && \text{(B10)}
\end{aligned}$$

For a fixed q, from (B10) 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 (B10) 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.

□

B2 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

$$\beta_2 := \gamma w c + b \tag{B11}$$

$$\beta_{1i} := \begin{cases} (1+q) - k(a-q) - (1-\gamma)w & \text{for } i = o, Y = (1+a) \\ 1 - k(a-q) - (1-\gamma)w & \text{for } i = m, Y = 1 \\ (1-q) - k(a-q) - (1-\gamma)w & \text{for } i = u, Y = (1-a) \end{cases} \tag{B12}$$

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

$$\lambda_i := \frac{\beta_2}{\beta_{1i}}. \tag{B13}$$

Then the derivatives of E read

$$\partial_c E = \beta_{1m}(1 - F(c)) - \gamma w \tag{B14}$$

$$\partial_q E = kE[\min(X, c)] \qquad > 0 \tag{B15}$$

$$\partial_c^2 E = -\beta_{1m} f(c) \qquad < 0 \tag{B16}$$

$$\partial_c \partial_q E = k(1 - F(c)) \qquad > 0 \tag{B17}$$

$$\partial_q^2 E = 0. \tag{B18}$$

Note that

$$P[\min(X, c) < \Omega] = \begin{cases} F[\Omega] & \text{for } \Omega < c \\ 1 & \text{for } \Omega \geq c. \end{cases} \tag{B19}$$

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

$$\frac{1}{10} < 1 - F(c^*) = \frac{\gamma w}{1 - k(a-q) - (1-\gamma)w} < \frac{1}{2}. \tag{B20}$$

from assumptions A2 and A3. We know

$$\lambda_u < \frac{3}{5}\mu, \tag{B21}$$

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

$$\frac{(c-\mu)}{\mu}\gamma w < (1 - a - w - \frac{b}{\mu}) - \frac{2}{5}(1 - a - w) \tag{B22}$$

$$\Rightarrow \frac{b}{\mu} + \frac{(c-\mu)}{\mu}\gamma w < \frac{3}{5}\left(1 - k(a-q) - q - (1-\gamma)w\right) - \gamma w \tag{B23}$$

$$\Leftrightarrow \frac{b + \gamma w c}{\beta_{1u}} < \frac{3}{5}\frac{\beta_{1u}}{\beta_{1u}}\mu \tag{B24}$$

$$\Leftrightarrow \lambda_u < \frac{3}{5}\mu. \tag{B25}$$

Hence the default probability takes the form

$$
\begin{aligned}
P &:= P[CF_\gamma(c,q) < 0 | Y = (1-a)] && \text{(B26)}\\
&= P\left[\min(X,c) < \frac{\beta_2}{\beta_{1u}} \middle| Y = (1-a)\right] = F[\lambda_u]. && \text{(B27)}
\end{aligned}
$$

Let

$$
Q := f(\lambda_u)\lambda_u \tag{B28}
$$

With

$$
\partial_c \lambda_i = \lambda_i \frac{\gamma w}{\beta_2} \tag{B29}
$$

$$
\partial_q \lambda_i = (-\lambda_i^2)\frac{(k+\delta_i)}{\beta_2} \text{ with } \delta_i = \begin{cases} 1 & \text{for } i = o \\ 0 & \text{for } i = m \\ -1 & \text{for } i = u, \end{cases} \tag{B30}
$$

then

$$
\begin{aligned}
\partial_q Q &= [f'(\lambda_u)\lambda_u + f(\lambda_u)]\,(\partial_q \lambda_u) && > 0 && \text{(B31)}\\
\partial_c Q &= [f'(\lambda_u)\lambda_u + f(\lambda_u)]\,(\partial_c \lambda_u) && > 0. && \text{(B32)}
\end{aligned}
$$

Subsequently

$$
\begin{aligned}
\partial_c P &= f(\lambda_u)(\partial_c \lambda_u) = \frac{\gamma w}{\beta_2} Q && > 0 && \text{(B33)}\\
\partial_q P &= f(\lambda_u)(\partial_c \lambda_u) = \frac{(1-k)}{\beta_2}\lambda_u Q && > 0. && \text{(B34)}
\end{aligned}
$$

Note that

$$
\begin{aligned}
\partial_q Q &= (\partial_q P)\Big[1 + \underbrace{\frac{\mu - \lambda_u}{\sigma}\frac{\lambda_u}{\sigma}}_{=:\tau}\Big] = (\partial_q P)(1+\tau) && \text{(B35)}\\
\partial_c Q &= (\partial_c P)(1+\tau). && \text{(B36)}
\end{aligned}
$$

With $\lambda_u < \mu$ from (B21),

$$
\begin{aligned}
\partial_c^2 P &= \frac{\gamma w}{\beta_2}\left(\partial_c Q - \frac{\gamma w}{\beta_2} Q\right) = \left(\frac{\gamma w}{\beta_2}\right)^2 f'(\lambda_u)\lambda_u^2 && > 0 && \text{(B37)}\\
\partial_c \partial_q P &= \frac{\gamma w}{\beta_2}(\partial_q Q) && > 0 && \text{(B38)}\\
\partial_q^2 P &= \frac{(1-k)}{\beta_2}\lambda_u\left(2f(\lambda_u) + f'(\lambda_u)\lambda_u\right)(\partial_q \lambda_u) && > 0. && \text{(B39)}
\end{aligned}
$$

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 (B17) there is a smooth function, $c^E(q)$ that parameterizes $\{\partial_c E = 0\}$ and is uniquely characterized by

$$(\partial_q \partial_c E)(\partial_q c^E) + \partial_c^2 E = 0 \;\Leftrightarrow\; \partial_q c^E = -\frac{\partial_c^2 E}{\partial_q \partial_c E} > 0, \tag{B40}$$

where the inequality follows from (B16) and (B18).

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 (B34), there is a smooth function, $c^P(q)$, that parameterizes $\{P = \alpha\}$. As above and using (B33) and (B34) for the inequality, it follows that

$$(\partial_q P)(\partial_q c^P) + \partial_c P = 0 \;\Leftrightarrow\; \partial_q c^P = -\frac{\partial_c P}{\partial_q P} < 0. \tag{B41}$$

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,

$$\mathcal{L} = E[CF] + \lambda \left(P[CF < 0] - t - \alpha \right), \tag{B42}$$

read for non-negative t

$$\partial_c E + \lambda \partial_c P = 0 \tag{B43}$$
$$\partial_q E + \lambda \partial_q P = 0 \tag{B44}$$
$$P[CF < 0] + t = \alpha \tag{B45}$$
$$t\lambda = 0. \tag{B46}$$

For a binding constraint the optimality condition thus reads

$$\frac{\partial_c E}{\partial_q E} = \frac{\partial_c P}{\partial_q P}. \tag{B47}$$

Let

$$L := (\partial_c E)(\partial_q P) - (\partial_q E)(\partial_c P). \tag{B48}$$

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 (B16), (B34), (B14), (B38), (B17), (B33), (B15) and

(B37) we have

$$\partial_c L = \underbrace{(\partial_c^2 E)}_{<0}\underbrace{(\partial_q P)}_{>0} + \underbrace{(\partial_c E)}_{>0}\underbrace{(\partial_c \partial_q P)}_{>0} - \underbrace{(\partial_c \partial_q E)}_{>0}\underbrace{(\partial_c P)}_{>0} - \underbrace{(\partial_q E)}_{>0}\underbrace{(\partial_c^2 P)}_{>0} \tag{B49}$$

and, additionally with (B39) and (B18),

$$\partial_q L = \underbrace{(\partial_q \partial_c E)}_{>0}\underbrace{(\partial_q P)}_{>0} + \underbrace{(\partial_c E)}_{>0}\underbrace{(\partial_q^2 P)}_{>0} - \underbrace{(\partial_q^2 E)}_{=0}\underbrace{(\partial_c P)}_{>0} - \underbrace{(\partial_q E)}_{>0}\underbrace{(\partial_c \partial_q P)}_{>0}. \tag{B50}$$

We first show

$$\partial_q L > 0 \qquad \text{on} \qquad \{L = 0\}. \tag{B51}$$

From (B50), it suffices to show

$$(\partial_q E)(\partial_c \partial_q P) < (\partial_c E)(\partial_q^2 P) \tag{B52}$$

$$\overset{L=0}{\Leftrightarrow} (\partial_c E)\frac{\partial_q P}{\partial_c P}(\partial_c \partial_q P) < (\partial_c E)(\partial_q^2 P) \tag{B53}$$

$$\Leftrightarrow (\partial_q P)(\partial_c \partial_q P) < (\partial_c P)(\partial_q^2 P) \tag{B54}$$

$$\Leftrightarrow \frac{\gamma w}{\beta_w} Q \frac{1-k}{\beta_2}\lambda_u\left[\lambda_u f'(\lambda_u) + f(\lambda_u)\right](\partial_q \lambda_u) < \frac{\gamma w}{\beta_2} Q \frac{1-k}{\beta_2}\lambda_u\left[\lambda_u f'(\lambda_u) + 2f(\lambda_u)\right](\partial_q \lambda_u) \tag{B55}$$

$$\Leftrightarrow 0 < f(\lambda_u), \tag{B56}$$

which is true.

We now show

$$\partial_c L < 0 \qquad \text{on} \qquad \{L = 0\}. \tag{B57}$$

From (B88) is suffices to show

$$\Big[(\partial_c E)(\partial_c \partial_q P) - (\partial_q E)(\partial_c^2 P) + (\partial_c^2 E)(\partial_q P)\Big]\frac{(\partial_c P)}{(\partial_c E)} < 0. \tag{B58}$$

Using $L = 0$, i.e., (B47), we have

$$(\partial_c E)(\partial_c \partial_q P) - (\partial_q E)(\partial_c^2 P) = \frac{(\partial_c E)}{(\partial_c P)}\Big[(\partial_c P)(\partial_c \partial_q P) - (\partial_q P)(\partial_c^2 P)\Big] \tag{B59}$$

$$= \frac{(\partial_c E)}{(\partial_c P)}\left(\frac{\gamma w}{\beta_2}\right)^2 \frac{1-k}{\beta_2} f(\lambda_u)^2 \lambda_u^3 \tag{B60}$$

and

$$(\partial_c^2 E)(\partial_q P) = \frac{(\partial_c E)}{(\partial_c P)}\frac{(\partial_c^2 E)}{\partial_c E}\left[(\partial_q P)(\partial_c P)\right] \tag{B61}$$

$$= \frac{(\partial_c E)}{(\partial_c P)} \frac{(-\beta_{1m}) f(c)}{\beta_{1m}(1 - F(c)) - \gamma w} f(\lambda_u) \lambda_u^2 f(\lambda_u) \lambda_u \left(\frac{\gamma w}{\beta_2} \right) \frac{1-k}{\beta_2} \tag{B62}$$

$$\leq (-1) \frac{(\partial_c E)}{(\partial_c P)} \frac{\gamma w}{\beta_2} \frac{1-k}{\beta_2} f(\lambda_u)^2 \lambda_u^3 \frac{f(c)}{(1 - F(c))}. \tag{B63}$$

Hence

$$\left[(\partial_c E)(\partial_c \partial_q P) - (\partial_q E)(\partial_c^2 P) + (\partial_c^2 E)(\partial_q P) \right] \frac{(\partial_c P)}{(\partial_c E)} \leq \frac{1-k}{\beta_2} \frac{\gamma w}{\beta_2} f(\lambda_u)^2 \lambda_u^3 \left[\frac{\gamma w}{\beta_2} - \frac{f(c)}{1 - F(c)} \right] < 0, \tag{B64}$$

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

$$\left[\frac{\gamma w}{\beta_2} - \frac{f(c)}{1 - F(c)} \right] < 0 \Leftarrow \frac{f(\mu)}{1 - F(\mu)} \geq \frac{\gamma w}{\gamma w \mu + b} \tag{B65}$$

$$\Leftrightarrow \sqrt{\frac{2}{\pi}} \frac{1}{\sigma} \geq \frac{\gamma w}{\gamma w \mu + b} \tag{B66}$$

$$\Leftrightarrow b \geq \gamma w \left[\sqrt{\frac{\pi}{2}} \sigma - \mu \right], \tag{B67}$$

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 (B51) and (B57), we have

$$(\partial_q L)(\partial_q c^L) + \partial_c L = 0 \;\Leftrightarrow\; \partial_q c^L = -\frac{\partial_c L}{\partial_q L} > 0. \tag{B68}$$

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).

□

B3 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

$$\partial_\gamma \partial_c E = (\partial_\gamma \beta_1)(1 - F(c)) - w = -wF(c) \qquad < 0 \tag{B69}$$
$$\partial_\gamma \partial_q E = k(\partial_\gamma E[\min(X, c)]) \qquad = 0. \tag{B70}$$

With

$$\partial_\gamma \lambda = \frac{w}{\beta_2}\lambda(c - \lambda). \tag{B71}$$

also

$$\partial_\gamma P = f(\lambda)(\partial_\gamma \lambda) = \frac{w}{\beta_2}(c - \lambda)Q \qquad > 0 \tag{B72}$$

$$\begin{aligned}
\partial_\gamma \partial_q P &= \frac{1-k}{\beta_2}\left[\partial_\gamma(\lambda Q) - \frac{wc}{\beta_2}(\lambda Q)\right] && \text{(B73)}\\
&= \frac{1-k}{\beta_2}\left[\lambda(\partial_\gamma Q) - \frac{\lambda w}{\beta_2}(\lambda Q)\right] && \text{(B74)}\\
&= \frac{1-k}{\beta_2}\Big[\lambda(1+\tau)(\partial_\gamma P) - \underbrace{\frac{w}{\beta_2}(c-\lambda)Q}_{\partial_\gamma P}\,\lambda\frac{\lambda}{(c-\lambda)}\Big] && \text{(B75)}\\
&= \frac{1-k}{\beta_2}\lambda\left[(1+\tau) - \frac{\lambda}{(c-\lambda)}\right](\partial_\gamma P) && \text{(B76)}\\
\partial_\gamma \partial_c P &= \frac{w}{\beta_2}\left[\gamma \partial_\gamma Q + \left(1 - \frac{\gamma wc}{\beta_2}\right)Q\right] && \text{(B77)}\\
&= \frac{w}{\beta_2}\left[\gamma(1+\tau) + \frac{b}{w}\frac{1}{(c-\lambda)}\right](\partial_\gamma P). && \text{(B78)}
\end{aligned}$$

Rearranging (B37) yields

$$\partial_c^2 P = \frac{\gamma w}{\beta_2}\left(\partial_c Q - \frac{\gamma w}{\beta_2} Q\right) \tag{B79}$$

$$= \frac{\gamma w}{\beta_2}(\partial_c P)(1+\tau) - \left(\frac{\gamma w}{\beta_2}\right)^2 Q \tag{B80}$$

$$= \frac{\gamma w}{\beta_2}(1+\tau)(\partial_q P)\frac{(\partial_c P)}{(\partial_q P)} - \frac{\gamma w}{\beta_2}(\partial_c P) \tag{B81}$$

$$= \frac{\gamma w}{\beta_2}(1+\tau)\frac{\gamma w}{1-k}\frac{1}{\lambda}(\partial_q P) - \frac{\gamma w}{\beta_2}(\partial_c P). \tag{B82}$$

We have

$$\partial_\gamma L = \underbrace{(\partial_\gamma \partial_c E)}_{<0}\underbrace{(\partial_q P)}_{>0} + \underbrace{(\partial_c E)}_{>0}(\partial_\gamma \partial_q P) - \underbrace{(\partial_\gamma \partial_q E)}_{=0}\underbrace{(\partial_c P)}_{>0} - \underbrace{(\partial_q E)}_{>0}\underbrace{(\partial_\gamma \partial_c P)}_{>0} \tag{B83}$$

$$= (\partial_\gamma \partial_c E)(\partial_q P) + Z \tag{B84}$$

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

$$G := \frac{1}{\lambda}\left[(\partial_c E)(1+\tau)\frac{\gamma w}{\beta_2}\lambda - k(1-F_c)\frac{\gamma w}{1-k} - (\partial_q E)\tau\frac{\gamma w}{\beta_2}\frac{\gamma w}{1-k}\right] \tag{B85}$$

and

$$H := k(1-F_c) - (\partial_c E)\frac{\lambda^2}{(c-\lambda)}\frac{(1-k)}{\beta_2} - (\partial_q E)\frac{\gamma w}{\beta_2}\left(1 + \frac{b}{\gamma w(c-\lambda)}\right). \tag{B86}$$

At the same time for $\partial_c L$, we have with (B88)

$$\partial_c L = (\partial_c^2 E)(\partial_q P) + N \tag{B87}$$

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,

$$
\begin{aligned}
\partial_c L &= \left[(\partial_c^2 E) + G\right](\partial_q P) && \text{(B88)} \\
&=: \tilde{G}(\partial_q P). && \text{(B89)}
\end{aligned}
$$

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

$$
\partial_\gamma\partial_c E + (\partial_c^2 E)(\partial_\gamma c^E) = 0 \overset{\text{(B69),(B16)}}{\Rightarrow} \partial_\gamma c^E = -\frac{\partial_\gamma\partial_c E}{\partial_c^2 E} < 0. \tag{B90}
$$

Likewise,

$$
\partial_\gamma P + (\partial_c P)(\partial_\gamma c^P) = 0 \overset{\text{(B72),(B33)}}{\Rightarrow} \partial_\gamma c^P = -\frac{\partial_\gamma P}{\partial_c P} < 0. \tag{B91}
$$

Likewise, from (B57) and (B51) we have

$$
\partial_\gamma L + (\partial_c L)(\partial_\gamma c^L) = 0 \Leftrightarrow \partial_\gamma c^L = -\frac{\partial_\gamma L}{\partial_c L} < 0 \quad \text{on} \quad \{L = 0\}. \tag{B92}
$$

Step 3: $|\partial_\gamma c^L| < |\partial_\gamma c^P|$ and $|\partial_\gamma c^E| < |\partial_\gamma c^P|$.
From (B88) and (B84), we have

$$
\begin{aligned}
\partial_\gamma L &= (\partial_\gamma\partial_c E)(\partial_q P) + Z && \text{(B93)} \\
&= (\partial_\gamma\partial_c E)(\partial_q P) + \left[\tilde{G}\lambda\frac{(1-k)}{\gamma w}\right](\partial_\gamma P) + H(\partial_\gamma P) - (\partial_c^2 E)\lambda\frac{(1-k)}{\gamma w}(\partial_\gamma P) && \text{(B94)} \\
&= \tilde{G}\frac{(\partial_q P)}{(\partial_c P)}(\partial_\gamma P) + H(\partial_\gamma P) + \Bigg[\underbrace{(\partial_\gamma\partial_c E)\frac{\partial_q P}{\partial_\gamma P} - (\partial_c^2 E)\lambda\frac{(1-k)}{\gamma w}}_{:=R}\Bigg](\partial_\gamma P) && \text{(B95)} \\
&= \partial_c L\frac{(\partial_\gamma P)}{(\partial_c P)} + (H+R)(\partial_\gamma P), && \text{(B96)}
\end{aligned}
$$

with

$$R = (\partial_\gamma \partial_c E)\frac{\partial_q P}{\partial_\gamma P} - (\partial_c^2 E)\lambda \frac{(1-k)}{\gamma w} \tag{B97}$$

$$= (\partial_\gamma \partial_c E)\frac{\partial_q P}{\partial_\gamma P} - (\partial_c^2 E)\frac{\partial_q P}{\partial_c P}. \tag{B98}$$

Hence,

$$-\partial_\gamma c^L = \frac{\partial_\gamma L}{\partial_c L} = \frac{\partial_\gamma P}{\partial_c P} + \frac{(H+R)(\partial_\gamma P)}{(\partial_c L)} = -\partial_\gamma c^P + (H+R)\underbrace{\frac{(\partial_\gamma P)}{(\partial_c L)}}_{<0 \text{ on } \{L=0\}}, \tag{B99}$$

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

$$|\partial_\gamma c^L| < |\partial_\gamma c^P| \Leftrightarrow -\partial_\gamma c^L < -\partial_\gamma c^P \Leftrightarrow (H+R) > 0. \tag{B100}$$

Similarly,

$$-\partial_\gamma c^E = \frac{(\partial_\gamma \partial_c E)}{(\partial_c^2 E)} = \frac{\partial_\gamma P}{\partial_c P} + \frac{(\partial_c \partial_\gamma E) - (\partial_\gamma P)/(\partial_c P)(\partial_c^2 E)}{(\partial_c^2 E)} = -\partial_\gamma c^P + R\underbrace{\frac{(\partial_\gamma P)}{(\partial_c^2 E)(\partial_q P)}}_{<0}, \tag{B101}$$

and from step 2

$$|\partial_\gamma c^E| < |\partial_\gamma c^P| \Leftrightarrow -\partial_\gamma c^E < -\partial_\gamma c^P \Leftrightarrow R > 0. \tag{B102}$$

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

Claim: $R > 0$.
Proof of claim.

$$R = (\partial_\gamma \partial_c E)\frac{\partial_q P}{\partial_\gamma P} - (\partial_c^2 E)\frac{\partial_q P}{\partial_c P} \tag{B103}$$

$$= -F_c(1-k)\frac{\lambda}{(c-\lambda)} + \beta_1 f_c \frac{(1-k)}{\gamma w}\lambda \tag{B104}$$

$$= \frac{(1-k)\lambda}{(1-F_c)}\Big[-\frac{F_c(1-F_c)}{(c-\lambda)} + \underbrace{\frac{\beta_1}{\gamma w}(1-F_c)}_{>1 \text{ since } \partial_c E > 0} f_c\Big] \tag{B105}$$

$$\geq \frac{(1-k)\lambda}{(1-F_c)}\Big[-\frac{1}{4(c-\lambda)} + f_c\Big] \tag{B106}$$

From (B21), assumption A2 and A1, we have

$$(c-\lambda) > c - \frac{3}{5}\mu > \frac{2}{5}\mu > 2\sigma. \tag{B107}$$

From assumption A3, we know $c < \mu + (5/4)\sigma$, hence $f_c > 1/(8\sigma)$. Plugged into (B106), this yields $R > 0$.

Claim: $(H + R) > 0$.
Proof of claim. From (B21) we have $(c - \lambda) > (1/3)c$, hence

$$1 + \frac{b}{\gamma w(c-\lambda)} \leq \frac{\gamma w + 3b/c}{\gamma w} \leq \frac{3\beta_2/c}{\gamma w}. \tag{B108}$$

Thus, we have

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

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

$$\frac{f_\mu}{(1-F_\mu)} = \sqrt{\frac{2}{\pi}}\frac{1}{\sigma} \approx 0.79\frac{1}{\sigma} \geq \frac{3}{4}\frac{1}{\sigma}, \tag{B109}$$

the expression in brackets is positive if

$$\frac{\lambda}{(c-\lambda)}\frac{1}{\beta_2}(\beta_1 - \gamma w) \leq \frac{3}{4}\frac{1}{\sigma} \tag{B110}$$

$$\Leftrightarrow \frac{(\beta_1 - \gamma w)}{(\beta_1 - q)}\frac{3}{4}\sigma \leq (c - \lambda). \tag{B111}$$

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

$$\frac{(\beta_1 - \gamma w)}{(\beta_1 - q)}\frac{3}{4} \leq 2 \Leftrightarrow \frac{q}{w} - \gamma \leq \frac{(\beta_1 - \gamma w)}{3w}, \tag{B112}$$

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

$$a \leq \frac{4}{9}(1-w) - \frac{1}{3}kh_{max} \tag{B113}$$

$$\Leftrightarrow a \leq \frac{1}{9}(1-w) + \frac{1}{3}(1 - w - kh_{max}) \tag{B114}$$

$$\Rightarrow \bar{\gamma}_{\min} \geq \frac{a}{w} - \frac{(\beta_1 - \gamma w)}{3w}. \tag{B115}$$

From (B109), 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

$$\mathbb{D} := \Big\{(\gamma, q, c) | \gamma \in [\gamma_{min}, \gamma_{max}], q \in [q_{min}, a], c \in \mathbb{R}^+\Big\} =: \mathbb{D}_1 \times \mathbb{D}_2 \times \mathbb{D}_3 \tag{B116}$$

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

$$\mathbb{C}^{LP} := \{L = 0\} \cap \{P = \alpha\}. \tag{B117}$$

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

$$rank \begin{pmatrix} DL \\ DP \end{pmatrix} = 2. \tag{B118}$$

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

$$\det \begin{pmatrix} \partial_c L & \partial_q L \\ \partial_c P & \partial_q P \end{pmatrix} = (\partial_c L)(\partial_q P) - (\partial_q L)(\partial_c L) < 0. \tag{B119}$$

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

$$\{\gamma_{min}, \gamma_{max}\} \times \mathbb{D}_2 \times \mathbb{D}_3 \quad \cup \quad \mathbb{D}_1 \times \{q_{min}, a\} \times \mathbb{D}_3. \tag{B120}$$

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,

$$\begin{aligned} c^P(\gamma_2, q^{LP}(\gamma_1)) \approx c^P(\gamma_1, q^{LP}(\gamma_1)) + \varepsilon\partial_\gamma c^P &= c^L(\gamma_1, q^{LP}(\gamma_1)) + \varepsilon\partial_\gamma c^P \\ &< c^L(\gamma_1, q^{LP}(\gamma_1)) + \varepsilon\partial_\gamma c^L \approx c^L(\gamma_2, q^{LP}(\gamma_1)), \end{aligned} \tag{B121}$$

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.

C Appendix: Data Appendix

C1 Cleaning BTR KUG

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

I 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). I 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.

C2 Cleaning Dafne

Before merging firm financial information from Dafne to the employment data at the IAB, I 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. I 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) I restrict attention to firms that are likely not just holdings. In particular, I 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), I 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)*. I demand that information on cash flow, cash and equity is available in 2019 *(16,400)*.

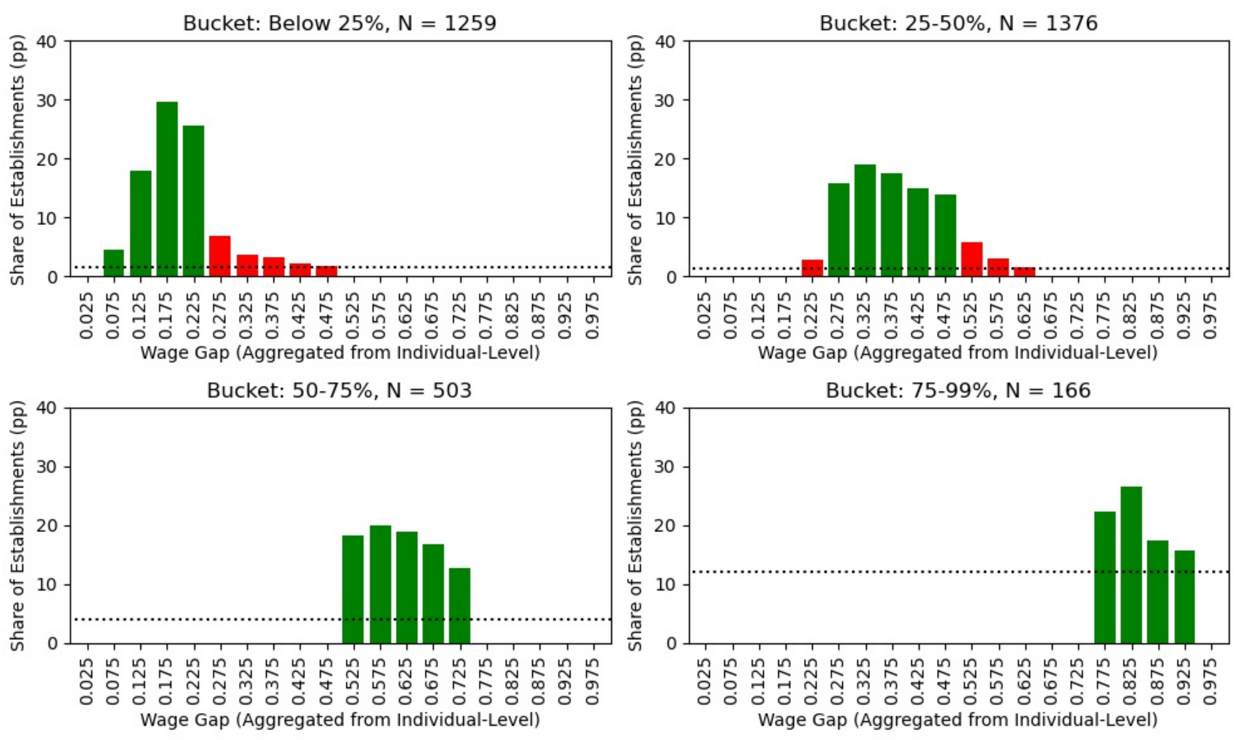
I consolidate information on FX gains and FX losses across two accounting formats (*Umsatzkostenverfahren* and *Gesamtkostenverfahren*) and two FX reporting schemes (*Aufwendungen/ Erträge aus Währungsumrechnung*, *Währungsgewinne/ Währungsverluste*). I identify which of the two FX schemes is the predominant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

C3 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, I have individual-level information on the wage gap. I aggregate this individual-level information to the establishment level and confirm that it aligns well with the described bucketed variable as depicted in the following figure.

Figure A.10: STW Usage Intensity from Establishment-Level vs. Individual-Level Data



Notes: This figure shows, for establishments for which individual-level information is available in 2020, per bucket of the establishment-level variable wage gap the distribution of the relative wage gap aggregated from individual-level information. Green bars indicate that the variable from aggregated individual-level data falls in the same bucket as the establishment-level variable. No information below the dotted line is available due to data protection (less than 20 establishments).

C4 Keyword-Based Classification of Derivatives Use (Firms' Reports)

I 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 I conduct a text analysis to identify mentions of FX hedging instruments. The reports are in German.

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

2) I search for explicit mentions of words indicating FX hedging. Specifically, as first pattern, I 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) I count raw occurrences of each pattern. Aditionally, I 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, I 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) I use the highest classification across the two patterns (*combined classification value*), except when one pattern has only negated mentions in which case I set the combined classification value to 1.

6) I classify a firm as using FX derivatives in a year if the combined classification value is at least two.

C5 AI-based Classification of Active FX Management (Firms' Reports)

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

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

3) I 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."

C6 Keyword-Based Classification of FX Service Provision (Banks' Reports)

I have manually downloaded annual reports for 7,360 bank-year observations. I 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 $[-20\%, 20\%]$. 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.

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

3) A bank is classified as having stopped offering FX derivatives in-house if it reported positive amounts outstanding at any point since 2010 but none thereafter (until 2018).

4) Anecdotal evidence suggests that some banks delegated their FX business to other banks within their banking group (Savings Banks Financial Group for savings banks, German Cooperative Financial Group for cooperative banks). I check whether commissioned trading in connection to FX derivatives or membership in S-International (part of the Savings Banks Financial Group) is mentioned in annual reports; this is the case for 144 institutions.

5) I classify a firm as being connected to a bank that continued offering derivatives if the firm is connected to a bank that offered FX derivatives at some point and neither stopped nor delegated.