Do Firms Hedge Human Capital?*

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Abstract

We find that firms whose staffing buffer exposes them to more risk pull back on adjustable financial risks. This buffer—expected excess labor capacity (precautionary labor)—lets firms meet uncertain demand, but its committed wage bill raises financial-distress risk. We measure precautionary labor from German short-time-work records during eased-access episodes, when otherwise-hidden idle labor becomes observable. Among export-oriented SMEs, which have major currency exposure, firms with more precautionary labor leave less foreign-exchange risk unhedged. This holds when instrumenting precautionary labor with occupation-based training and hiring frictions tied to firm-specific human capital. A newsvendor model with financial distress formalizes the mechanism.

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1 Introduction

Workers are not always busy. When hiring or training takes time, a firm facing uncertain demand may employ more workers than it currently needs: a buffer it draws on when demand is high and absorbs as hoarded labor when demand falls.[1] This expected excess labor capacity, which we call *precautionary labor*, is a labor-side analog to precautionary debt capacity (Aydin and Kim, 2026) and to expected unused capacity more broadly (Amberg, Friberg, and Syverson, 2026). It rarely shows up in firm data: idle workers stay on the payroll and look no different from busy ones. It is also costly: because the buffer's wage bill is committed ahead of demand, it raises a firm's operating leverage and its exposure to bad states (Simintzi, Vig, and Volpin, 2015; Donangelo, Gourio, Kehrig, and Palacios, 2019). A firm that carries more of it takes on more risk, and if its capacity to bear risk is limited, it may have to reduce risk somewhere else. This paper asks whether firms with more precautionary labor carry less risk on other margins.

Precautionary labor is hard to study precisely because it is hard to observe, and we recover it from an unusual policy window. Germany's short-time work program lets firms retain idle workers at the program's expense, but access is normally tightly restricted. When eligibility was eased by decree in 2020, more than 40% of the firms in our sample used the program—well above the financial-crisis peak—many with revenues close to their 2019 level. Firms operating roughly normally thus documented idle hours that would ordinarily go unrecorded, revealing the staffing buffer they hold. We test whether firms offset this labor-side risk by carrying less currency risk—a major, adjustable exposure for exporters—in a setting where both sides of the trade-off are measurable. Beyond the staffing buffer this setting makes visible, export-oriented German SMEs must disclose the foreign-exchange (FX) risk they leave unhedged, along with their risk-management policies, in their annual reports. Such firm-level hedging information is scarce, even for widely used instruments (Alfaro, Calani, and Varela, 2024).

We find that firms with more precautionary labor leave less of their FX risk unhedged. Instrumenting precautionary labor with occupation-based training and hiring frictions, a one-standard-deviation increase in precautionary labor lowers FX-induced cash-flow volatility by about 0.8 of a standard

1 This terminology follows the classic labor-hoarding literature, including Oi (1962); Okun (1963); Burnside, Eichenbaum, and Rebelo (1993); Giroud and Mueller (2017). See Biddle (2014) for an overview.

deviation. Both precautionary labor and hedging are persistent firm characteristics, so we read this as a contrast across firm types, not as the effect of a contemporaneous staffing choice. Firms appear, in other words, to hedge their human capital indirectly: those whose staffing buffer exposes them to more risk pull back on a financial margin they can adjust.

We formalize the trade-off between precautionary labor and unhedged price risk in a stylized two-period model that nests a risk-neutral newsvendor capacity choice (Arrow, Harris, and Marschak, 1951) in a financial-distress environment, where committing to labor ahead of demand raises default risk (as in Arellano, Bai, and Kehoe (2019)). To this benchmark we add two elements: a second, hedgeable price risk, and firms that differ in their reliance on *inflexible labor*: workers who take time to find and train and so must be committed before demand is known. Precautionary labor is the expected unused part of this inflexible labor. Because the distress constraint makes firms behave as if risk-averse—as private SMEs with financing frictions are likely to be (Froot, Scharfstein, and Stein, 1993)—precautionary labor and unhedged price risk compete for scarce risk-bearing capacity.

Solving the model across the firm distribution delivers three predictions for the cross-section we observe. First, firms with more precautionary labor hedge more and so leave less price risk unhedged. Second, the heterogeneity behind this—firm-specific human capital, which raises reliance on inflexible labor—fixes the sign of the first stage: firms with more firm-specific human capital hold more precautionary labor, and we later instrument precautionary labor with it, combining firms' occupational composition with occupation-level training and hiring frictions. Third, the comparative statics predict the substitution is stronger for firms with higher wages, more volatile demand, larger fixed obligations, or costlier hedging.

To test these predictions, we assemble a firm-level dataset linking labor and financial information. On the labor side, German matched employer-employee records provide granular occupational composition, and administrative short-time-work records report unused employee hours at monthly frequency. For 2020, the data also allow us to observe short-time work usage at the worker level. On the financial side, we pair data on balance sheets, income statements (including data on FX transaction income), and bank relationships, with hand-collected annual reports, from which we additionally infer FX hedging strategies by text analysis.

We measure precautionary labor from firms' short-time work (STW) usage during eased-access episodes, after controlling for the year-on-year revenue change. STW is a job-retention scheme for otherwise healthy firms: admitted firms can flexibly reduce hours while documenting the unused hours in detail, and employees are compensated for most of the wage loss. It is this documentation that makes otherwise-hidden idle labor observable. Since the start of the STW data in 2009, eligibility was eased by decree twice, in 2009 and again in March 2020. We build the baseline measure from 2020 and use 2009 as a robustness check.

We first validate this interpretation. A central concern is that STW in 2020 may capture mostly pandemic disruption rather than precautionary labor. We address this concern by excluding the lockdown months, by restricting the sample to firms with a stable output window, and by focusing on the tradable-goods sector, which is less reliant on personal interactions. Using worker-level records for 2020, we further show that idle labor is concentrated in occupations that rely more on occupational training—even within the same firm and month—which supports interpreting the measure as retained, hard-to-adjust labor rather than only a transitory demand shortfall.

Before testing the model's cross-sectional predictions, we verify its central premise: that precautionary labor acts like operating leverage, raising a firm's exposure to demand shocks. Consistent with this prediction, we show that changes in profitability comove more strongly with industry-wide upturns and downturns for firms with precautionary labor than for firms without it. Precautionary labor therefore appears to amplify exposure to demand fluctuations. Yet firms with more precautionary labor do not have higher total cash-flow volatility, measured as the standard deviation of cash flows scaled by revenue over 2010-2019. This pattern suggests that firms offset labor-side risk by reducing risk along another margin.

We study FX risk as one such margin. From accounting data on FX transaction income (Adams and Verdelhan, 2022), we build two measures of FX-induced cash-flow volatility that are net of hedging and so capture the risk firms leave unhedged. The margin is central for German SMEs. It is adjustable at low operational cost: firms in our sample are linked to 2.6 banks on average, and both large German banks and regional banks routinely provide FX and interest-rate derivatives to commercial clients. Unlike total cash-flow volatility, this FX-induced volatility falls with precautionary labor, and the pattern survives a rich set of controls proxying for export structure, profitability, and treasury sophistication.

To connect the pattern to the labor-market friction in the model, we instrument precautionary labor with occupation-based variation in how costly labor is to adjust: our main measure combines firms' occupational employment shares with the importance of vocational training in each occupation, a proxy for longer training and harder replacement in tight labor markets (Dustmann and Schönberg, 2012; Eckardt, 2026). As alternative, we fix occupational composition in 2013 ahead of a shortened outcome window and use occupation-level labor shortages as a second instrument. The identifying assumption is that, conditional on the export share and observable characteristics, the measure of firm-specific human capital is unrelated to a firm's FX risk except through the labor it carries. We document that occupation shares are stable, uncorrelated with the export share, and that our measures are balanced on size and access to hedging across the median. In the first stage, firms with more training-intensive occupations hold more precautionary labor, as the model predicts. The second-stage estimates are robust across instruments and larger than the OLS estimates, consistent with attenuation.

We next look at explicit hedging actions rather than residual exposure. We measure FX-derivative use with a keyword-based indicator and an AI-assisted text classification, both from the appendices of annual reports and validated against each other. About a quarter of the firms use FX derivatives, and those with more precautionary labor are more likely to be among them. Extending the AI classification to operational hedging—for example, matching the currency of costs and revenues—about a fifth of the non-users hedge this way instead, so the genuinely unhedged group is smaller than derivative use alone would imply. These text-based measures are coarser than our accounting measure, but they point the same way as the unhedged-risk result.

Our paper contributes to two literatures. First, it contributes to work on labor risk and corporate financial policy. A large literature shows that fixed labor expenses create labor-induced operating leverage and make firms more sensitive to shocks (Donangelo, Gourio, Kehrig, and Palacios, 2019). Prior work shows that labor commitments shape firms' financing and adjustment margins, especially leverage (Simintzi, Vig, and Volpin, 2015; Serfling, 2016; Kuzmina, 2023), but also cash holdings (Ghaly, Anh Dang, and Stathopoulos, 2017) and other operating choices such as contract mix (Acabbi and Alati, 2021).[2] We build on this literature by shifting attention from labor commitments as a fixed cost to the staffing buffer that creates those commitments. We model precautionary

2 More broadly, this literature examines how labor-market frictions affect corporate financing decisions. See, e.g., Agrawal and Matsa (2013); Campello, Gao, Qiu, and Zhang (2018); Schmalz (2018); Caggese, Cuñat, and Metzger (2019); Baghai, Silva, Thell, and Vig (2021).

labor as expected unused inflexible labor and measure retained unused labor capacity using eased-access short-time work. By tracing labor-induced operating leverage back to the staffing decision that creates it, we link a real-side staffing buffer directly to corporate risk management. This complements Barrot, Martin, Sauvagnat, and Vallée (2024), who show that easing financing frictions leads firms to hoard more skilled labor, concentrated in high-skill, hard-to-fill occupations—running from financing to labor, the reverse of our channel.

Second, the paper contributes to the literature on nonfinancial firms' hedging of foreign-exchange risk. Especially for smaller nonfinancial firms, derivatives are not primarily a trading activity but a way to manage risks arising from commercial operations and treasury financing. Yet evidence on their FX derivatives usage remains limited, and little is known about how hedging choices relate to firms' real operations (Alfaro, Calani, and Varela, 2023; Levin-Konigsberg, Stein, Averell, and Castañon, 2023). Recent work uses administrative derivatives data collected under the European Market Infrastructure Regulation (EMIR) (Hau, Hoffmann, Langfield, and Timmer, 2021; Hommel and Piquard, 2026) but such data cannot be linked to German matched employer-employee records under the current regulatory environment. We instead extend accounting-based measures of FX-induced cash-flow volatility as in Adams and Verdelhan (2022) to privately held firms and complement them with text-based measures of FX derivatives usage and broader FX risk-management strategies from annual reports. The contribution is therefore not only to document hedging among private firms, but to show that residual FX exposure and active FX management are systematically related to firms' real-side staffing buffers.

The closest paper is Huang, Huang, and Zhang (2019), who find that U.S. public firms scoring higher on employee treatment hedge more of their foreign sales with currency derivatives—a commitment channel in which firms hedge for their workers' sake. Our channel is instead a real-side one: firms whose technology forces a costly labor buffer carry more operating leverage and substitute toward less FX risk. We also replace an employee-treatment rating with a direct measure of retained idle labor and occupation-based onboarding frictions, and study the residual risk firms leave unhedged.

The remainder of the paper is organized as follows. Section 2 presents the model. Section 3 describes the data. Section 4 introduces the institutional background on short-time work in Germany, constructs and validates the measure of precautionary labor, and characterizes firms and workers with precautionary labor. Section 5 asks whether the measure behaves like labor-induced operating leverage. Section 6 studies whether firms offset this exposure by leaving less FX risk unhedged. Section 7 relates the pattern to occupation-based onboarding frictions. The final section concludes.

2 A Newsvendor Model with Financial Distress

We formalize the channel in a stylized two-period model with a risk-neutral newsvendor capacity choice (Arrow, Harris, and Marschak, 1951), embedded in a financial-distress environment similar to the example in Arellano, Bai, and Kehoe (2019). Within it we define precautionary labor, and add a hedgeable price risk and firm-specific human capital as the source of firm heterogeneity, mapping to our empirical design.

The key trade-off is illustrated in Panel (a) of Figure 1. A firm faces demand uncertainty and an unrelated, hedgeable price risk, and must commit inflexible labor before demand is known, setting its capacity. More inflexible labor raises expected cash flow but, as a fixed cost, also raises the default probability. Because the firm must keep that default probability below a threshold—which makes it behave as if risk-averse (Froot, Scharfstein, and Stein, 1993)—it offsets the higher default risk from more inflexible labor by hedging the price risk more. More precautionary labor therefore goes with less unhedged price risk.

2.1 Setup and Definition of Precautionary 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 (*inflexible labor*) and workers who can be employed flexibly depending on demand (*flexible labor*). A firm is characterized by a level of *firm-specific human capital* $\gamma \in [\gamma_{min}, \gamma_{max}], \gamma_{max} \leq 1$, fixed by its technology, which determines the relative importance of inflexible labor in the production process. Specifically, a firm with γ requires γc inflexible labor and $(1-\gamma)c$ flexible labor to produce output c.

In $t = 0$, firm γ chooses its inflexible labor γc and consequently *capacity* c under demand uncertainty. In $t = 1$, the firm receives *orders* $X \sim \mathcal{N}(\mu, \sigma^2)$.[3] The firm serves orders up to its chosen capacity c, producing $\min(X, c)$. The firm knows the expectation μ and variance σ^2 of the normally distributed random variable X with cdf F. No capital exists, and the wage per unit of labor is $w \in [0, 1]$.

Price uncertainty. The firm faces a second type of uncertainty: unrelated price risk, which is realized in $t = 1$. To fix ideas, suppose the firm exports at a price denominated in foreign currency. Let Y be the value in the firm's home currency, a discrete random variable equal to 1 in expectation that takes three values: for some fixed $a \in (0, 1)$, $P[Y = (1 - a)] = P[Y = (1 + a)] = p$ and $P[Y = 1] = 1 - 2p$, for $p \in [0, 1/2]$. Thus, $Var[Y] = 2pa^2$. Suppose X and Y are independent.[4]

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 the remaining *unhedged 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 $k \in (0, 1)$. We assume that per-unit hedge costs kh scale with output rather than capacity: the firm fixes the hedge level h at $t = 0$ but adjusts the hedged volume once demand is known.[5]

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

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

4 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 (lower Y) is likely associated with reduced foreign demand (lower X). A positive comovement between X and Y is expected to intensify the model mechanism.

5 Two arrangements fit this. With a financial hedge, a baseline agreement with the firm's relationship bank may hedge a fixed fraction of revenue (the hedge level), with the notional adjustable once demand is realized. With operational hedging, the firm may ex ante invoice a fixed fraction of output in its home currency (the hedge level), weakening its bargaining position and reducing the margin. In both, cost scales with output.

quantity produced, $\min(X, c)$, multiplied by the per-unit price net of costs (expression in brackets), minus the wage bill for inflexible labor, γwc, and some other fixed costs b. Importantly, whereas flexible labor costs scale with output, inflexible labor costs scale with the capacity level set at $t = 0$.

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

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

The constraint is a break-even condition: in the bad exchange-rate state the firm defaults when realized sales fall below $\lambda = (b + \gamma wc)/(\,1 - (a-h) - kh - (1-\gamma)w\,)$, the ratio of fixed obligations (numerator) to the per-unit margin (denominator). Because the inflexible wage bill γwc enters the numerator, a firm that relies more on inflexible labor (a higher γ) must sell more to break even. Committing to labor ahead of demand is thus a fixed cost that raises the firm's *operating leverage*: it widens the range of demand shortfalls that push the firm into default, making cash flow more sensitive to demand.

Precautionary labor. *Precautionary labor (pl)* is defined as expected unused inflexible labor. A firm that hired γc inflexible labor expects to need $\gamma E[\min(X, c)]$ inflexible labor for production. The difference between the two represents expected unused inflexible labor. Formally, for a firm with firm-specific human capital γ that chooses capacity c,

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

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

6 We derive the model solution analytically for the constraint in (2). In the numerical simulation, we also consider the (more intuitive) constraint $P[CF_\gamma < 0] \leq \alpha$ (see Panel (c) of Appendix Figure C.1) 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.

capacity.

2.2 Risk-Neutral Benchmark

As a starting point, consider the firm's unconstrained problem:

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

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

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

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

Proof. See Appendix A1. □

In the absence of the constraint, the firm does not hedge. Hedging has no benefit in expectation, because it does not change the expected exchange rate but is costly.

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 inflexible labor (RHS). The marginal expected benefit (LHS) is the expected price net of flexible-labor costs, $(1-(1-\gamma)w)$, times the probability that the firm benefits from the increased capacity, i.e., that orders exceed the current capacity, $(1-F(c^*(\gamma)))$. This is the first-order condition of the standard newsvendor model (see, e.g., Arrow, Harris, and Marschak (1951) and Butters (2019)), with $1-\gamma w/(1-(1-\gamma)w)$ as critical fractile.

When the firm chooses the price, the critical fractile can also be moved by the markup, as in contemporaneous work by Amberg, Friberg, and Syverson (2026). Here, with the price taken as given and total unit labor cost fixed at w, it is moved instead by the split of that cost into inflexible (γw) and flexible ($(1-\gamma)w$) labor—operating leverage rather than markup.

2.3 Analytical Solution Across the Firm Distribution

We now analytically solve the constrained problem (2) for a fixed level of firm-specific human capital γ and, as a second step, as a function of γ.

We restrict attention to firms in the following region of the parameter space:

$$\mu \geq 5\sigma \qquad \text{(Demand not too volatile)} \qquad \text{(A1)}$$
$$\gamma_{max} < \bar{\gamma}_{max} = (1 - w - kh_{max})/w \qquad \text{(Service level } F(c^*) \text{ above 50\%)} \qquad \text{(A2)}$$
$$\gamma_{min} > \bar{\gamma}_{min} = (1 - w)/(9w) \qquad \text{(Service level } F(c^*) \text{ below 90\%)} \qquad \text{(A3)}$$
$$a \leq (4/9)(1 - w) - (1/3)kh_{max} \qquad \text{(FX risk not too large)} \qquad \text{(A4)}$$
$$k \leq \bar{k} \qquad \text{(Hedging cheap enough to use at margin)} \qquad \text{(A5)}$$
$$(3/5)\mu > (b + \gamma_{max}wc^*)/(1 - a - (1 - \gamma_{max})w) \qquad \text{(Default as a tail event)} \qquad \text{(A6)}$$

The six assumptions keep the firm in a realistic, well-behaved region. Assumption A1 limits demand volatility: for a normal distribution, it implies that a drop in demand by 20% relative to the expected level has a likelihood of less than 16%. Assumptions A2 and A3 restrict attention to firms whose optimal service level $F(c^*)$ lies between 50% and 90%. Assumptions A4 and A5 restrict the amplitude of exchange-rate fluctuations and the per-unit costs of hedging. Assumption A6 keeps the break-even demand λ (fixed obligations over the per-unit margin, evaluated without hedging) below three-fifths of the expected level, so the firm defaults only in the lower tail of demand.

Proposition 1 (**Solution for a single firm**). *Suppose Assumptions A1–A6 and consider a firm with firm-specific human capital γ. Then* (2) *has a unique solution* $(c^{opt}(\gamma), h^{opt}(\gamma))$ *which is one of four cases:*

a) the constraint does not bind, and the solution is the unconstrained optimum of Lemma 1;

b) the constraint binds with no hedging, $h^{opt}(\gamma) = 0$;

c) the constraint binds at an interior hedge level, where the solution equates the shadow cost of capacity to the shadow cost of hedging,

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

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

Proof. See Appendix A2. □

The interior solution in Proposition 1 states that capacity and hedging are complements. Increasing capacity and decreasing hedging are both profitable in expectation, but they come with a cost as they raise the default probability. Hence, at the optimum the shadow cost of increasing capacity equals the shadow cost of decreasing hedging: more capacity and *less* hedging compete for the firm's scarce risk-bearing capability.

Which case occurs depends on the level of γ. Panels (c)–(e) of Appendix Figure C.1 illustrate the model solution for three increasing levels of γ. In each panel, points that satisfy the relevant conditions (constraint, unconstrained optimality, Lagrange optimality) are depicted in red, yellow, and blue, respectively. As γ increases, the constraint becomes stricter, foreshadowing the next proposition, which characterizes the model solution as a function of γ.

Proposition 2 (**Solution across the firm distribution**). *Suppose Assumptions A1–A6 and consider a continuum of firms $\gamma \in [\gamma_{min}, \gamma_{max}]$. The optimal case is monotone in γ: there exist thresholds $\gamma_1 < \gamma_2 < \gamma_3$ such that a firm is in case a) of Proposition 1 for $\gamma \leq \gamma_1$, case b) for $\gamma_1 < \gamma \leq \gamma_2$, case c) for $\gamma_2 < \gamma \leq \gamma_3$, and case d) for $\gamma_3 < \gamma$. Not all four regimes need occur (e.g. if $\gamma_{max} < \gamma_3$).*

Proof. See Appendix A3. □

An increase in γ shifts a larger fraction of the wage bill from variable to fixed costs. Higher fixed costs raise the default probability and make the constraint stricter, so as γ increases the solution transitions from unconstrained to constrained.

2.4 Numerical Simulation and Empirical Predictions

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

Comovement. Across firms with different γ, precautionary labor and unhedged exchange-rate variance move in opposite directions. Panel (b) of Figure 1 plots both against γ (left and right axes): as γ rises, precautionary labor increases while the unhedged exchange-rate variance falls. The intuition is the interior-optimum trade-off of Proposition 1: more capacity and less hedging compete for the firm's scarce risk-bearing capability. Thus, a firm that commits more to precautionary labor has less room to bear unhedged FX risk and hedges more.

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

Mechanism. Panel (b) of Figure 1 is also informative about the source of the variation in precautionary labor: as γ rises, optimal precautionary labor increases. A higher γ shifts the wage bill toward fixed costs and raises the default probability, so under the binding constraint the firm lowers capacity (Panel (a) of Appendix Figure C.1). This is similar to Arellano, Bai, and Kehoe (2019), here triggered by a higher γ rather than higher demand volatility. The inflexible share of the workforce nonetheless rises and this effect dominates, so precautionary labor increases overall (Panel (b) of Appendix Figure C.1).

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

Comparative statics. Figure 2 plots the precautionary-labor–volatility relationship directly: optimal precautionary labor on the x-axis, the unhedged exchange-rate variance on the y-axis. It shows how it shifts under various parameter changes. Each line traces firms with different levels of firm-specific human capital under otherwise fixed model parameters.

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

Because the comovement arises only where the constraint binds (at the unconstrained optimum, precautionary labor and hedging are independent, Lemma 1), this heterogeneity offers a direct test of the mechanism, which we take to the data in Section 6.

3 Data

Our analysis combines firm- and worker-level data on German firms from six sources. Three are administrative records of the German Federal Employment Agency: establishment-level monthly short-time work (STW) receipt, matched employer-employee data, and, for a subset of firms, individual-level STW receipt in 2020. We combine these with commercial firm-level financial data, which we enrich with hand-collected, text-analysis-based measures of their FX hedging and export activity. Finally, we add occupation-level information on vocational training and hiring difficulties.

Establishment-level information on monthly STW receipt. We use establishment-level data on monthly STW receipt (BTR-KuG) from 2009 to 2020 (see also Kagerl (2026)). Establishments that have been admitted to the STW program submit a detailed monthly application for reimbursement to the employment agency. The data we use are compiled for statistical purposes by the Statistics of the Federal Employment Agency (*Statistik der Bundesagentur für Arbeit: Tabellen, Realisierte Kurzarbeit, Nürnberg, Oktober 2021, Daten mit einer Wartezeit von bis zu 5 Monaten (ohne Hochrechnung)*). The close link to the operational system on which the actual payment of benefits is based ensures high data reliability. The data provides monthly information on whether an establishment receives STW benefits, the number of short-time workers, the wage bill gap (i.e., the difference between the regular wage bill and the reduced wage bill, incorporating hours changes due to STW), and the hours gap in worker equivalents (in buckets; for details, see Appendix B3).

We convert the data to a monthly panel and merge it with the Establishment History Panel (Ganzer, Schmucker, Stegmaier, and Wolter, 2023), which since 1999 contains information on all establishments in Germany with at least one marginal part-time employee as of June 30 each year. This merge allows us to ensure basic consistency (see Appendix B1 for details) and to add location and industry information. We then aggregate the establishment-level data to the firm level, assigning to each firm the location and industry of its largest establishment.

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

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

Individual-level information on monthly STW receipt. We further use individual-level data on STW receipt (PKUG Personen in Kurzarbeit, see Kagerl (2026) for an overview). While benefit payment data are recorded at the establishment level because employers are reimbursed for STW benefits, monthly applications *(Abrechnungslisten)* list the employees in STW. These typically manual applications were digitized for March 2020 to December 2021 and linked to individual employment biographies. A comprehensive validation procedure at the employment agency cross-checked the resulting information against establishment-level records and employment biographies for each month. We follow the procedure in Brinkmann, Jäger, Kuhn, Saidi, and Wolter (2025) (see Appendix therein for details). We exclude firms for which the validation procedure is infeasible, i.e., when no 1:1 or 1:n mapping exists between the establishment applying for STW and the employer in the Social Security Records (dropping ca. 15% of firms). The data provide, for all individuals employed at establishments using STW sometime in 2020, a monthly likelihood of STW receipt, classified as 0%, small (0-20%), medium (20-50%), high (above 50%), or 100%. In our analysis, individuals are classified as being in STW if this likelihood exceeds 50%.

Firm-level financial information. Our main data on firm-level financial information comes from the commercial database Dafne, provided by Bureau van Dijk/Creditreform. Dafne contains financial information on German firms since 2008 and is the underlying source for data on German firms in BvD's Orbis dataset (see, e.g., Jäger, Schoefer, and Heining (2021) and Moser, Saidi, Wirth, and Wolter (2026) for recent work with BvD data matched to German administrative data). Appendix B2 summarizes how we assemble and clean the firm-level financial data. Beyond annual balance-sheet and income-statement information at the unconsolidated level, we also observe the banks that firms have banking relationships with (*relationship banks*). To gauge FX derivatives provision by those banks, we match the banks to SNL Fundamentals by name and add information on their annual outstanding amount of FX derivatives to clients, obtained from text analysis of banks' hand-collected annual reports (see Appendix B6 for details).

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

Occupation information. We rely on occupation-level information on hiring difficulties and the prevalence of vocational training. Information on the prevalence of vocational training comes from the 2019 wave of the Occupational Panel (see Grienberger, Janser, and Lehmer (2023) for details), which is based on the universe of German Social Security Records and the Federal Employment Agency's occupational expert database (*Berufenet*). Information on hiring difficulties comes from a bi-annual classification by the German Federal Employment Agency that compiles a list of so-called shortage occupations (see Section 7.1 for details). We use the classification as of December 2019.[7]

Sample selection. We start from all German firms that report an unconsolidated income statement—specifically, revenue—in both 2019 and 2020 and satisfy basic data-consistency requirements, following Kalemli-Özcan, Sørensen, Villegas-Sanchez, Volosovych, and Yeşiltaş (2024) (16,323 firms; see Appendix B2 for the details).[8] We match these firms to the confidential employment data, aggregated to the firm level, with a match rate of 71%. We then restrict to firms with at most 20 establishments

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

8 The count is not larger because a firm need not publish an income statement in Germany unless it exceeds at least two of three size thresholds (12 million EUR revenue, 6 million EUR assets, and 50 employees).

(11,482 firms) and to those whose employment in the annual reports roughly coincides with the aggregated establishment-level employment at the IAB (within a tolerance of -20% to +100%; 10,071 firms), ensuring that sample firms employ primarily in Germany. Following standard practice, we drop regulated utilities (WZ 2008 sections D and E), financial firms (section K), and public-service firms (section O), leaving 9,145 firms.

Two further restrictions define the core sample we use. First, we keep firms whose 2020 year-on-year revenue change lies between -20% and $+20\%$ (6,913 firms). This window isolates firms whose output stayed somewhat close to normal in 2020, needed for our measure of precautionary labor. Second, for the final sample we keep firms that report FX transaction income in at least two years between 2010 and 2019 and for which the 2019 export share is available (2,310 firms). This selects firms with recurring foreign-currency exposure; we assess how it shapes representativeness in the summary statistics below.

Summary statistics. Table 1 reports summary statistics for the final sample. To gauge representativeness, we compare the sample to two benchmarks: the universe of German firms that report revenue (16,323 firms in Panel (a) of Appendix Table D.1) and firms with a stable output window in 2020 that are successfully matched at the IAB (6,913 firms in Panel (b) of Appendix Table D.1).

The median sample firm is larger than the median German firm and the median matched firm (in parentheses) (230 vs. 145 (165) employees), more profitable (ROA of 6% vs. 4% (4%)), and more capital intensive (value added per employee of 0.09 vs. 0.07 (0.08) million EUR). It also exports more than the median German firm (export share of 45% vs. 34%), consistent with the sample containing a higher share of *Hidden Champions* (Simon, 1996): highly specialized SMEs that lead globally in niche, often produce-to-order, markets with substantial export activity. Their workforces are similar to those of the matched firms—similar in average age (43.0 vs. 43.3 years) and tenure (10.1 vs. 9.3 years)—but are better paid (median daily wage of 131 vs. 116 EUR) and more concentrated in production rather than service roles (43% vs. 16%), in line with this specialized-manufacturing profile.

This selection toward specialized, export-oriented firms is mirrored in the industry composition: the share of manufacturing firms roughly doubles relative to the matched IAB sample (62% vs. 33%; cf. Appendix Figure C.3). The largest sectors are manufacturing, trade, information and communication, and professional, scientific, and technical activities. Because these sectors depend less on in-person interaction, they were less exposed to the pandemic to begin with, which further alleviates the concern that lockdowns bias our measure for precautionary labor.

4 Measuring Precautionary Labor from STW Usage

Precautionary labor—expected unused inflexible labor as in (3)—has few empirical analogs, since the idle capacity implied by a firm's staffing decision is not recorded in standard firm data. We recover it from short-time work (STW): when the government temporarily eased eligibility by decree, firms operating roughly normally drew on a program that is otherwise tightly restricted, documenting idle hours that would ordinarily go unobserved. Our measure is average STW intensity during the 2020 eased-access episode among firms whose output remained close to its 2019 level. Several pieces of evidence indicate that it captures retained idle labor rather than pandemic disruption alone, including within firms: holding firm and month fixed, STW concentrates in occupations with longer training requirements.

4.1 Institutional Context: Short-Time Work (STW) in Germany

Short-time work (STW) allows firms to cut hours temporarily while the employment agency replaces part of the lost wage. Using it requires admission to the scheme and meeting several eligibility criteria.

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

Firms file an application for admission (*Anzeige*) to the STW scheme and, if approved, can choose monthly whether and to what extent to use STW. Typically, the maximum duration of STW is 12 months. Each month, firms submit detailed documentation (*Abrechnungslisten*) on

STW usage at the employee level to obtain reimbursement. Payments from the employment agency are provisional until the end of the STW period, when a final examination (*Abschlussprüfung*) verifies whether eligibility criteria were met throughout the scheme's duration.

Access rules. 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).

4.2 STW during Eased-Access Episodes

During eased-access episodes, STW was used more broadly than usual, including by firms not in evident difficulty. We describe the timing and breadth of this take-up here.

Usage across time. Two features of STW usage in 2020 point to usage by firms beyond acute distress. First, its scale was unprecedented: Panel (a) of Figure 3 shows that over 40% of sample firms used STW in 2020 and usage remained high into the second half of the year, after lockdown measures had ended in May (cf. Appendix Figure C.2). Second, firms using STW during the eased-access episode in 2020 were not as severely hit as their counterparts during the eased-access episode in 2009. Panel (b) of Figure 3 compares the median year-on-year revenue growth of STW users and non-users, with status assigned year by year. STW users typically have lower revenue growth than non-users, but their 2020 decline is far milder than the sharp drop STW users experienced in the 2009 financial crisis. That so many firms drew on STW without the steep drop-and-rebound of 2009 is hard to attribute to temporary distress alone, and is consistent with firms retaining otherwise-idle workers.

Industry-wide monthly usage. This view is corroborated within industries using data at monthly frequency. We compare monthly industry-level revenue with STW usage among sample firms in the same industry, focusing on the largest sectors in the sample. Appendix Figure C.2 plots monthly industry-wide revenue (blue, left-hand scale) against STW usage (red, right-hand scale) for 2019 and 2020. In each sector in panels (a)-(d), economic activity had largely recovered by the second half of 2020, yet STW usage remained high.

Qualitative evidence. Survey evidence further reinforces the view that restrictions were temporarily lifted in 2020. In an anonymized survey by proIAB of eight local employment-agency branches, conducted in August 2022, branches report that mentioning "COVID" sufficed for admission to the STW scheme in the first month after March 2020, when the unprecedented volume of applications had to be processed operationally. Procedures tightened slightly by the summer of 2020, following a general directive, but until the second lockdown in mid-December 2020 a brief reference to COVID-19 typically sufficed without further documentation. Pre-pandemic proof-of-eligibility requirements were reinstated in 2021.

4.3 Construction of a Measure of Precautionary Labor

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

$$\text{Unused Inflexible Labor}_{im} := \frac{\text{Short-Time Work in Employee Equivalents}_{im}}{\text{Number of Employees}_{im}}. \tag{7}$$

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

$$\text{STW Usage Intensity}_{i,\mathcal{M}} := \sum_{m\in\mathcal{M}} \frac{1}{|\mathcal{M}|} \text{ Unused Inflexible Labor}_{im}, \tag{8}$$

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

$$\text{Precautionary Labor}_i := \text{STW Usage Intensity}_{i,\,\text{eased-access episode}}. \tag{9}$$

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

We take several steps to reduce the influence of COVID-related labor underutilization on the measure. First, we use the year-on-year revenue change in 2020 as a proxy for output declines due to the COVID-19 shock and control for it throughout.[9] Second, and as detailed below, we substantially restrict the sample in three ways. We exclude data from the lockdown months up to and including May when constructing the measure; we restrict the analysis to firms whose 2020 revenue is not too atypical (year-on-year revenue change in the range of $[-20\%, 20\%]$); we require data on FX transaction income, naturally focusing the analysis on sectors such as the tradable-goods sector, which are less reliant on personal interactions.

4.4 Beyond the COVID-19 Shock

Figure 4 links, at the firm level, STW usage in 2020 to the year-on-year revenue change, showing binned scatterplots of STW usage intensity against revenue changes. For firms that experienced a revenue drop, STW usage intensity is strongly associated with revenue changes. For firms with positive revenue growth, however, this association disappears, yet STW usage intensity remains at approximately 1-2% on average, regardless of the level of revenue growth. A similar pattern emerges for STW usage (binary) in Panel (b) of Figure C.4.

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

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

access restrictions, with only a modest correlation between STW usage and revenue declines.

4.5 Characteristics of Firms with Precautionary Labor

We use the new measure to shed light on the characteristics of firms that hold precautionary labor. Figure 5 plots coefficients from a regression of precautionary labor on various firm characteristics, comparing firms within the same industry and region and controlling for revenue changes.

Firms with higher levels of precautionary labor tend to be somewhat smaller, consistent with smaller firms having less access to internal labor markets than large firms (Cestone, Fumagalli, Kramarz, and Pica, 2024). Precautionary labor is not significantly related to leverage or to capital intensity (proxied by value added per employee), and only weakly negatively related to cash holdings and to pre-pandemic revenue growth. Return on assets (ROA) is markedly lower, which likely reflects residual negative selection into STW despite the eased access (Giupponi and Landais, 2023); we control for ROA in the analyses that follow. Firms with more precautionary labor sell more abroad, so we also control for the export share throughout. Taken together, these two facts—lower profitability but greater export activity—speak against reading our later finding as an artifact of weaker firms with little exposure: one would not expect weaker firms to export more, and a higher export share means greater, not lesser, exchange-rate exposure.

4.6 Evidence From Individual-Level Short-Time Work Receipt

A final piece of evidence uses individual STW receipt to ask which workers within a firm are placed on STW. If the measure captures retained inflexible labor, STW should fall disproportionately on workers in hard-to-adjust occupations which we proxy by occupations that require more training.

This is what we find. Using the individual-level data described in Section 3, workers with vocational training are 8 percentage points more likely to be on STW unconditionally (both with and without worker controls, columns 1 and 2) and 5 percentage points more likely within firm (columns 3 and 4). Because the within-firm comparison holds firm and month fixed, it reflects which workers a firm keeps idle rather than differences across firms or over time. In the remaining columns we replace individual-level information on vocational training with the prevalence of vocational training at the occupation level—the same occupation-level measure we use to construct our main instruments in Section 7—and find the same pattern. This worker-level concentration is the micro-analog of that instrument's first stage.

5 Link to Cash Flow Volatility

Holding precautionary labor has a real-option value (when demand is high) and increases operating leverage which should make firms that hold precautionary labor look riskier. This section documents that changes in profitability of firms with precautionary labor comove more strongly with changes in industry-wide demand: staffing buffers amplify exposure to both upturns and downturns. Yet these same firms show no higher total cash-flow volatility. Read together, the two facts point to an offset: firms appear to absorb the labor-side risk that more precautionary labor creates by reducing risk along another margin, which we take up in Section 6.

5.1 Larger Comovements of Cash Flow with Demand for Firms with Precautionary Labor

We use a firm-year panel in which profitability and demand vary over time, while a firm's precautionary-labor status is measured once and held fixed.

Empirical design. To empirically explore this upside potential of precautionary labor, we examine the difference in the comovement of profitability changes with demand changes between firms with and without precautionary labor and expect to find a stronger correlation for the former. Specifically, we estimate the following regression for year t and firm i in industry $s(i)$:

$$\Delta Y_{it} = \beta\, 1(\text{Precautionary Labor})_i \times \Delta\text{Demand}_{s(i)t} + \alpha_i + \alpha_{s(i)t} + \varepsilon_{it}, \tag{R1}$$

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

Sauer, Schasching, and Wohlrabe (2023) for details).

Results. Table 3 shows the results of regressions of the form (R1), using return on assets (ROA) in columns 1 to 3 and cash flow (CF) in columns 4 to 6 as a measure for firm-level profitability. Columns 1 and 4 do not include firm fixed effects but instead include *1(Precautionary Labor)* separately. We add firm fixed effects in columns 2 and 5 and year-by-industry-by-region 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 profitability with industry-wide demand for firms holding precautionary labor. In our preferred specification (column 3), a one-standard-deviation rise in industry demand raises the ROA of firms with precautionary labor by 5.7 percentage points ($= 0.664 \times 0.086$) more than that of comparable firms without it. The result also holds when using changes in cash flow instead of ROA in columns 4 to 6.

Robustness. The firm-year panel underlying Table 3 is unbalanced across the cycle: 78% of observations fall in upturns and only 22% in downturns (Panel (b) of Appendix Table D.2). To check that the result is not driven by this imbalance, and to confirm it under a sharper measure of demand, we turn to manufacturing, where a volume-based, normalized index of new orders is available monthly at a finer industry level. This panel is roughly balanced (49% upturns) but covers only about a quarter of the observations. Panel (a) of Appendix Table D.2 reproduces the stronger comovement using this order-based proxy.

5.2 No Association with Larger Overall CF Volatility

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

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

where *Precautionary Labor*$_i$ for firm i is defined as in Section 4, and $\mathbf{X}_i$ is a vector of control variables based on 2019 and fixed-effect dummies (industry by region). *CF Volatility* is defined as the standard deviation of CF scaled by revenue based on annual data from 2010 to 2019.

Panel (a) of Table 4 shows that firms with more precautionary labor do not exhibit higher total CF volatility. Columns 1-4 use the broadest sample possible not restricting to firms with FX information available yet (cf. Panel (b) of Appendix Table D.1). Column 1 uses a binary indicator whereas the remaining columns use the continuous measure on the left-hand side. Value added per employee and ROA are included in columns 3 and 4 to control for differences in capital intensity and productivity, yet there is still no statistically significant correlation with precautionary labor. Among the sample firms, precautionary labor is also not significantly correlated with total CF volatility (column 4). It is, however, significantly correlated with FX-induced CF volatility (columns 6 and 7), which we take up in the next section.

6 Unhedged Foreign Exchange (FX) Risk as One Adjustment Margin

One margin firms in the sample adjust is foreign-exchange risk. Using accounting data on FX gains and losses, we measure the cash-flow volatility firms leave unhedged: residual risk, net of any hedging. Firms with more precautionary labor leave less of it unhedged, unlike total cash-flow volatility; the relationship is robust to obvious alternative channels and varies across firms as the model's comparative statics predict.

Two measures of unhedged FX risk. We construct two measures of FX-induced CF volatility from the accounting variables FX gains and FX losses.[10] We calculate net FX gains scaled by revenue in year t,

$$\text{Net FX Gains}_t := (\text{FX Gains}_t - \text{FX Losses}_t)\,/\,\text{Revenue}_t, \tag{10}$$

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

$$\begin{aligned} \text{sd net gains} &:= \text{sd}\Big\{\text{Net FX Gains}_{2010}, \ldots, \text{Net FX Gains}_{2019}\Big\} \cdot 100 \\ \text{max net loss} &:= -\min\Big\{\min\{\text{Net FX Gains}_{2010}, \ldots, \text{Net FX Gains}_{2019}\}, 0\Big\} \cdot 100. \end{aligned} \tag{11}$$

Both measures are winsorized at the 1% and 99% level to remove outliers. The first measure provides

10 Adams and Verdelhan (2022) use similar accounting variables for publicly traded firms, and we demonstrate the approach's applicability also to private firms.

an intuitive starting point for measuring volatility. The second measure captures the largest loss induced by net FX positions and aligns more closely with heightened default risk from exchange-rate movements, the ultimate concern for risk-averse firms. Thus, it more closely maps to the constraint in the model.

The variables *FX Gains* and *FX Losses* record the revaluation of foreign-currency receivables and payables between invoicing and settlement, booked *after* any hedge revalues. Our measures therefore capture residual FX risk—the exposure firms leave unhedged—consistent with the model. A perfectly hedged firm records offsetting revaluations on the hedged item and on the hedge, leaving net FX gains unchanged; the two hedge-accounting methods permitted under the German Commercial Code (*Einfrierungs-* and *Durchbuchungsmethode*) treat the gross variables differently but yield identical net FX gains. Appendix B7 works through a numerical example, both unhedged and hedged.

FX risk material for these firms. FX risk is economically material for these firms. Appendix Figure C.5 shows that more than 10% recorded unhedged FX gains or losses exceeding 10% of annual profits in 2017 (Panel (a)).[11] Its salience also shows up at their banks: for many local relationship banks, FX derivatives are the leading derivative sold to commercial clients, with outstanding notionals above 15 billion EUR in 2016 (Panels (d) and (e) of Appendix Figure C.5). Furthermore, these variables likely understate total exposure: they capture revaluations between invoicing and payment but miss price changes before invoicing and the interim payments common in long-term contracts (e.g., machinery).[12]

Correlation holds with further controls. Firms with more precautionary labor have significantly lower FX-induced CF volatility on both measures (Panel (a) of Table 4, columns 6–7). Panel (b) shows this negative correlation is robust to the most direct channels through which a firm's occupational and production structure could shape FX exposure. Columns 1–2 report the baseline for both

11 Foreign-currency financing is unlikely to drive these patterns: BIS locational banking statistics show only 1.5% of bank claims and liabilities in Germany are denominated in non-euro currencies.

12 A German firm exporting to the US often operates through a US subsidiary, but FX gains and losses still accrue to the German parent when the subsidiary only distributes rather than produces: it buys from the parent at arm's-length prices denominated in USD, leaving the FX risk with the parent. Because the sample firms keep most of their employees in Germany, their foreign subsidiaries are plausibly distribution-only.

measures—*sd net gains* and *max net loss*—conditioning on firm size, profitability, and overall export share. The remaining columns add—one at a time and partly at the expense of a substantially smaller sample due to data availability—the share of exports outside the euro area (columns 3–4), import intensity (columns 5–6), and the number of relationship banks, a proxy for treasury sophistication and access to hedging (columns 7–8). These are the dimensions on which occupational composition might otherwise proxy for FX exposure rather than for precautionary labor. The coefficient on precautionary labor stays negative throughout and is significant in seven of the eight specifications. We read these as cross-sectional correlations: firms with more precautionary labor leave less FX risk unhedged, and the most obvious alternative dimensions of firm structure do not account for the pattern.

Heterogeneity along model comparative statics. So far we have established the model's first prediction: firms with more precautionary labor leave less FX risk unhedged. We now turn to the model's comparative statics, which predict where that correlation should be stronger or weaker. Appendix Table D.3 reports sample splits along four proxies for the model's parameters, including value added per employee as an additional control. Columns 1 and 2 show the correlation is weaker for firms with a low labor share, a proxy for the wage w in the model. For manufacturing firms, it is also weaker in industries with low demand volatility (columns 3 and 4), though this split rests on less than half of the sample.[13] We find no difference between firms with high and low leverage (columns 5 and 6).

The correlation also attenuates for firms with more than three relationship banks (columns 7 and 8). This is consistent with the model's comparative static for lower hedge costs, but it also points to unobserved firm characteristics as a source of bias. A larger number of relationship banks may proxy for more sophisticated risk management, which would independently lower both unhedged FX risk, through more effective hedging, and precautionary labor, through organizational practices that reduce employee idleness. Some firms employ staff dedicated to so-called "staff-level optimization," rotating employees across divisions to minimize downtime. Because this channel induces a positive comovement between the two, it would bias the OLS correlation toward zero.

13 We proxy industry demand volatility by the volatility of the value index of monthly incoming orders, 2010–2020, from the Federal Statistical Office of Germany (tables 42151-0002).

7 Labor-Market Rigidities Behind the Channel

The correlation in Section 6 is in line with the mechanism, but unobserved firm characteristics such as risk-management sophistication could drive both precautionary labor and hedging. Because precautionary labor is observed only during the 2020 eased-access episode, the design remains cross-sectional. This is defensible because we expect both precautionary labor and hedging policies to be fairly stable firm characteristics. Guided by the model's heterogeneity in firm-specific human capital, we now exploit labor-side rigidities as a source of exogenous variation, measured from the detailed occupational structure in the employer-employee data. The logic is simple: positions that take a long time to fill, because they require lengthy training or are hard to hire for, lead firms to hold more precautionary labor. We present robustness tests along several dimensions and, in addition, explore firms' hedging strategies using annual reports.

7.1 Identification Strategy

The model gives firm-specific human capital (FSHC) a clear role. Under risk-neutrality, FSHC determines how much inflexible, and hence precautionary, labor a firm holds but has no bearing on its hedging (Lemma 1); under risk-aversion, it shapes hedging too, through precautionary labor.

FSHC stems from the time it takes to train and hire workers: positions that require lengthy training or are hard to fill cannot be staffed on demand. We capture this with two shift-share-type instruments (Goldsmith-Pinkham, Sorkin, and Swift, 2020). Firms' occupational composition takes the role of shares, and occupation-specific onboarding difficulty maps to the shocks: lengthy training times (vocational-training-based FSHC) or lengthy hiring times (shortage-occupation-based FSHC) in a robustness. We then estimate the following 2SLS specification.

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

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

Occupation composition. Identification relies on the idea that firms' technologies are fixed, at least over some time window, and that technology determines each firm's occupational composition (as in Crouzet, He, Lyonnet, and Ma (2026)). Leveraging detailed occupation information available over time in the German matched employer-employee data, we compute year-end shares of employees by occupation for each firm. Following standard practice in the literature (see, e.g., Grienberger, Janser, and Lehmer (2023)), we define an *occupation* at the level of the occupational group (three-digit level) combined with the requirement level (fifth digit). The requirement level distinguishes between unskilled/semiskilled workers, skilled workers, specialists, and experts.

Table D.4 reports summary statistics for the largest occupations in the sample. Occupations in machine-building and -operating at the specialist level are the largest occupation group, with an average share of 10% in 2019 and 2018 among firms that have at least one employee in this occupation (1,571 firms in 2019). This masks substantial heterogeneity in the relevance of these occupations, with a share of 6% in the median firm and 25% at the 90th percentile. The picture remains very similar for 2018, already pointing toward a high degree of stability in firms' occupational compositions, which we test more formally later. The last two columns report, per occupation, the share of employees with vocational training (from the occupation panel) and an indicator for whether the occupation is classified as a shortage occupation, which we discuss further below.

Occupations with lengthy training time. To identify occupations whose onboarding times exceed the demand-forecast horizon, we turn to Germany's vocational-training system (Dustmann and Schönberg, 2012). Training is firm-based, not confined to vocational schools: workers with vocational training have completed an apprenticeship inside a firm, typically lasting about three years and supplemented by one or two days of classes per week. Firms have an incentive to build firm-specific knowledge during this period, because they expect to retain their apprentices afterward. Survey evidence shows that firms offer employment to apprentices in about 90% of cases (Mohr, 2015). As Eckardt (2026) show, the specific human capital such training delivers is costly and slow to rebuild, so positions in training-intensive occupations cannot be staffed on demand.

We define for firm i

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

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

Instrument validity. Instrument validity hinges on relevance and the exclusion restriction. Regarding relevance, a higher level of FSHC should be associated with more precautionary labor. Panel (a) of Table 5 reports the first stage for the vocational-training-based instrument: the coefficient is positive, consistent with the model, implying that a 100-basis-point increase in the share of employees in training-intensive occupations is associated with a 5-basis-point higher fraction of the workforce that is temporarily idle on average. The first-stage F-statistic (Kleibergen–Paap Wald; Andrews, Sock, and Sun (2023)) is 13.5. We report Anderson–Rubin confidence sets in the just-identified specifications.

The exclusion restriction requires that the instrument be uncorrelated with unobserved determinants of the relationship in (R3). Firm fixed effects are infeasible, so we always compare firms within the same industry and region and control for firm size and exposure to the COVID-19 shock (revenue change). Appendix Table D.5 splits firms at the median of each instrument and conducts a comparison-of-means in the last column. Panel (a) using the vocational-training based instrument shows that firms with high FSHC have on average lower leverage, lower cash holdings, and a lower capital intensity, proxied for by value added per employee. High- and low-FSHC firms are statistically indistinguishable in various size measures (assets, revenue, employees), as well as export activity (export share and the propensity to export to outside of Europe). They also do not differ in access to hedging: in links to the major large banks (*Deutsche Bank, Commerzbank, UniCredit*) nor in the probability of using FX derivatives in 2019, which speaks against differences in unobserved risk-management sophistication.

A specific concern is that the exclusion restriction would be violated if firms' exposure to global markets—and thus their exchange-rate-driven cash flow volatility—shaped their technology and hence their demand for employees across occupations. We address this in two ways. First, we control for the export share in all regressions. Second, we show that firms' occupational compositions are highly stable over time and do not vary systematically with the export share. Exploiting the panel dimension of our data, we identify each firm's three largest occupational groups in 2019 and trace their year-end shares over the preceding four years. Appendix Table D.6 shows that these shares are highly stable over time. In particular, in the specification including lagged export share—which reduces the sample due to limited export-share information over time—90% of the variation is explained by firm fixed effects, while year fixed effects have little explanatory power. In the specification with the most granular fixed effects, the shares are not correlated with the lagged export share.

7.2 Precautionary Labor Lowers Unhedged FX Risk

Our preferred estimate, identified jointly from both instruments, implies that a one-standard-deviation increase in precautionary labor lowers FX-induced cash-flow volatility by 0.8 standard deviations. The single vocational instrument yields a larger magnitude, 1.2 standard deviations. We start with the single-instrument specification based on vocational-training intensity, because its reduced form is directly interpretable and it can be rebuilt at earlier dates, which lets us test whether the result is an artifact of timing. We then add a second instrument, and the overidentification test does not reject.

Baseline with the vocational-training based instrument. Panel (a) of Table 5 reports the estimates: 2SLS in columns 3 and 4, alongside OLS (columns 1 and 2) and reduced-form estimates (columns 5 and 6). A one-standard-deviation increase in precautionary labor lowers FX-induced cash-flow volatility by 1.2 standard deviations ($= (13.837 \times 0.053)/0.584$), an effect that is statistically significant and mirrored in the strongly significant reduced form.[14] Figure 6 visualizes the design with the first stage in Panel (a) and the second stage in Panel (b); the slopes point to the same effect. We also depict the reduced form in Panel (c).

Robustness: timing. Precautionary labor is observed only during eased-access episodes, so a panel design is infeasible; the cross-sectional design is sensible as long as firm-level differences in precautionary labor are persistent. Two checks in Table 6 address the concern that our estimates

14 The 2SLS estimates exceed the OLS estimates in magnitude. Following Jiang (2017), this is consistent with attenuation in the OLS: omitted-variable bias—such as unobserved risk-management sophistication, which plausibly lowers employee downtime and improves hedging—biases the OLS toward zero, while reverse causality biases it away from zero. The relative magnitudes suggest the former dominates. This is consistent with the weaker OLS effect among firms with more than three relationship banks (Appendix Table D.3). A small partial R^2 of the excluded instruments could still inflate the 2SLS estimates even when the first-stage F is large.

may reflect the mechanical timing of the measurement of the instrument and the FX outcome rather than an underlying relationship.

First, in Panel (a) of Table 6, we rebuild the vocational-training-based instrument from 2013 data—firm-level occupation shares and occupation-level training intensity, both measured in 2013—and restrict FX-induced volatility to 2014-2020, strictly after the instrument's measurement window. Because precautionary labor is still inferred from the 2020 episode, we continue to control for the 2019–2020 revenue decline as a proxy for COVID-19 exposure, but draw assets and ROA from 2013. The OLS, 2SLS, and reduced-form estimates all hold, each somewhat larger in magnitude, by 30% (2SLS estimates) to 50% (reduced-form estimates).

Second, in Panel (b) of Table 6, we measure precautionary labor from the 2009 eased-access episode, controlling for Global Financial Crisis exposure through the 2009 year-on-year revenue change and for firm size and ROA in 2008. An overhaul of the occupational classification in 2011 makes it infeasible to fully reconstruct our occupation-level instrument for 2008, so here we fall back on the firm-level share of vocationally trained workers as a proxy—accepting the firm-level measurement we otherwise avoid, since no analogously constructed occupation-level alternative exists this far back. The effect again survives in the OLS, 2SLS, and reduced form, though the instrument substantially weakens (first-stage F-statistic of 5.3).

A second instrument based on occupation-specific shortages. So far we have relied on a single source of variation. We now add a second instrument, built on a different labor-market friction, which lets us test overidentifying restrictions. Some positions are hard to fill not because they require lengthy training, but because suitable workers are scarce in the market. We draw on the official classification of *shortage occupations* and define for firm i

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

The German Federal Employment Agency publishes a biannual list of shortage occupations (*Engpassberufe*) in which positions are structurally hard to fill, based on the occupation's vacancy duration, its ratio of unemployed to job postings, and its unemployment rate.[15] These criteria are

15 An occupation qualifies if its average vacancy duration is at least 30% above the overall average, the ratio of unemployed to job postings is below 2:1 for skilled workers and specialists (4:1 for experts), and its unemployment

designed to minimize the influence of hiring challenges specific to individual firms, such as poor working conditions or limited mobility among the unemployed. We enrich the federal classification (by requirement level, aggregated from the four-digit level to occupational groups) with an analogous classification at the regional (*Bundesland*) level.

For the shortage-occupation-based instrument, columns 1 and 2 of Table 7 report the 2SLS estimates.[16] The effect is the same sign and somewhat smaller: a one-standard-deviation increase in precautionary labor lowers FX-induced cash-flow volatility by 0.58 standard deviations ($= (6.343 \times 0.053)/0.584$). The instrument is strong, with an effective first-stage F-statistic (Montiel Olea–Pflueger, coinciding with Kleibergen–Paap in the just-identified case) of 22.2, higher than the 13.5 for the vocational instrument.

Both instruments: preferred specification. Columns 3 and 4 of Table 7 include both instruments. The effective first-stage F-statistic is 16.1, above the weak-instrument threshold (in the row below), and the overidentification test does not reject: the Hansen J p-value is 0.14 for the sd measure and 0.07 for the max measure, so the test passes at the 10% level for the sd measure and at the 5% level for the max measure. The estimate implies that a one-standard-deviation increase in precautionary labor lowers FX-induced cash-flow volatility by 0.77 standard deviations ($= (8.514 \times 0.053)/0.584$), which we regard as our most reliable estimate.

7.3 Hedging Strategies

Finally, we ask how the firms in our sample hedge FX risk, and whether the precautionary-labor channel also shows up in their observed hedging behavior. So far we have measured the FX risk firms leave *unhedged*, inferred from the standardized accounting item Net FX Gains; we now turn to the hedging actions themselves, measured from a text analysis of annual-report appendices. We use two measures—a keyword-based indicator and an AI-assisted classification of FX-derivative use. We validate the two against each other (Appendix B4) and extend the second approach to active FX management more broadly. We further ask whether the response operates through cash and leverage, alternative precautionary buffers.

rate is below 3%, subject to confirmation by an expert.

16 The analogous exercise of splitting firms by this measure is reported in Panel (b) of Appendix Table D.5.

FX derivatives usage as outcome. We can also use hedging behavior itself as the outcome. Panel (b) of Table 5 reports estimates with an indicator for FX-derivative use in 2019 as the dependent variable. More precautionary labor raises the propensity to hedge: the 2SLS coefficient is 6.36 and significant (accompanied by positive AR confidence bands), the reduced form is positive and significant with a coefficient of 0.28. The OLS estimate is close to zero, consistent with attenuation.[17] Because derivative use is an observed hedging action rather than an accounting inference, it offers a more direct check on the channel.

Who uses FX derivatives. Panel (a) of Table 8 compares firms that use FX derivatives with those that do not. Roughly 27% of firms report using FX derivatives in 2019. Users are larger on every size measure—the median user holds about twice the assets of the median non-user—and, unsurprisingly, are more export-oriented. Two comparisons are particularly interesting. First, users and non-users have indistinguishable import shares, which points to hedging of export receipts rather than import costs. Second, users maintain more relationship banks, and the difference comes from links to the large German banks rather than to local banks. Users and non-users are otherwise similar in leverage and in workforce age and wages.

Operational hedging among non-users. Panel (b) of Table 8 looks within the non-users, separating those that hedge operationally from those that appear genuinely unhedged. Not using derivatives need not mean a firm is unhedged: firms can hedge operationally, for example by matching the currency of costs and revenues or by invoicing in euro. Such strategies are firm-specific and hard to capture with keywords, so here we rely on the AI-assisted classification alone and treat the results with caution. About 20% of firms that do not use FX derivatives nonetheless report operational FX hedging strategies in their annual reports. Relative to other non-users, these operational hedgers have higher capital intensity, pay higher wages, and are more export-oriented. Their access to derivatives does not set them apart, suggesting operational hedging is a deliberate choice rather than a fallback for firms without access to derivatives markets.

Role of cash and leverage. Cash and leverage are alternative precautionary buffers, so we

17 The 2SLS coefficient is large relative to the 27% base rate of derivative use; because the outcome is binary and the estimator linear, the magnitude is best read as directional rather than as a literal probability.

ask whether the FX-hedging response is concentrated among firms that rely on them. Table D.7 interacts precautionary labor with indicators for high cash holdings and for low leverage, using both instruments, and the unhedged-FX-risk specification. The overidentification test does not reject and Sanderson–Windmeijer first-stage F statistics are reported below. The interaction terms are statistically insignificant throughout: we find no evidence that the effect is concentrated among cash-rich or low-leverage firms. We read this as ruling out cash and leverage as the margin through which the response operates, not as evidence that they are irrelevant.

8 Conclusion

Firms that hold a staffing buffer because their labor is hard to adjust carry more operating leverage and leave less FX risk unhedged: they appear to hedge their human capital indirectly. Two measurement steps, each a hurdle until now, make this visible. We recover precautionary labor from German firms' use of short-time work during eased-access episodes, when normally-idle labor surfaces in administrative data, and we measure their FX risk management from standardized accounting items and the text of annual reports. Bringing the staffing buffer and the residual currency risk into view in the same sample is what lets us tie a real-side staffing decision to a financial risk-management one.

Our setting is specific by design: export-oriented German SMEs, for which currency risk is a major exposure and FX hedging is cheap and readily available through a bank-based financial system. The underlying trade-off, though, is not specific to currency risk. When a real-side rigidity raises a firm's risk and its capacity to bear risk is limited, the firm retreats on whichever margin is least costly to adjust. FX is that margin here; for a firm selling at home it would be another. What the results point to is a pecking order of risk-reduction strategies—financial and real—whose ordering depends on the institutional and product-market environment the firm operates in.

The share of output that depends on specialized, hard-to-replace human capital is unlikely to shrink. As it grows, more firms will carry precautionary labor not by choice but by the nature of their technology, and with it the operating leverage we document. The pressing question is which margin they use to absorb the resulting risk. Firms in our setting reach for a financial one, leaving less FX risk unhedged, at little cost to their real operations. But the same risk-bearing constraint could instead be met by pulling back on risky, growth-relevant investment such as R&D or entry into new markets. The two responses look alike on a firm's balance sheet yet differ sharply in their consequences for innovation and growth. Understanding when firms substitute toward cheap financial hedging rather than retrenching on real investment, and how financial development shapes that choice, is an open question relevant for innovation and growth.

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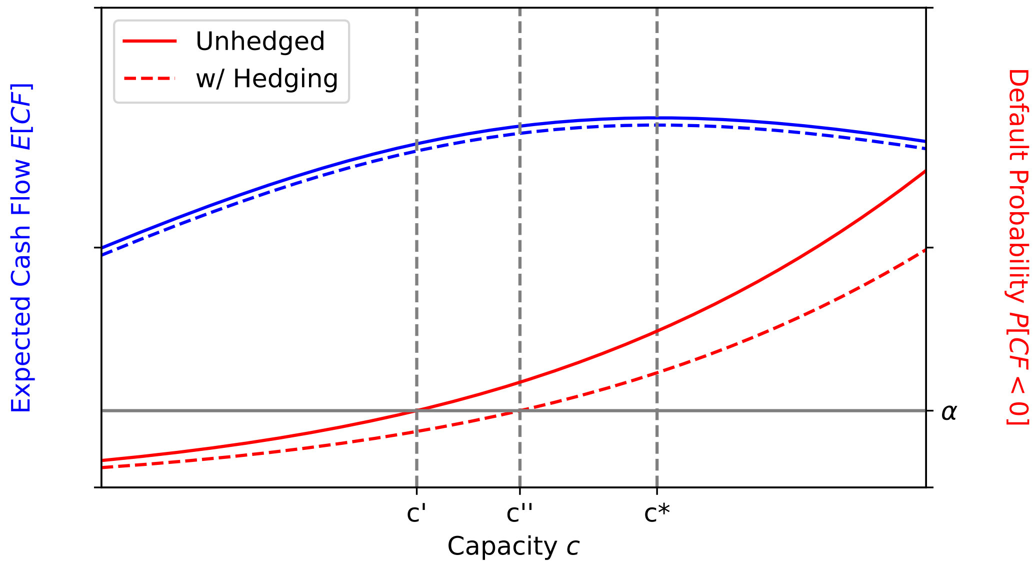
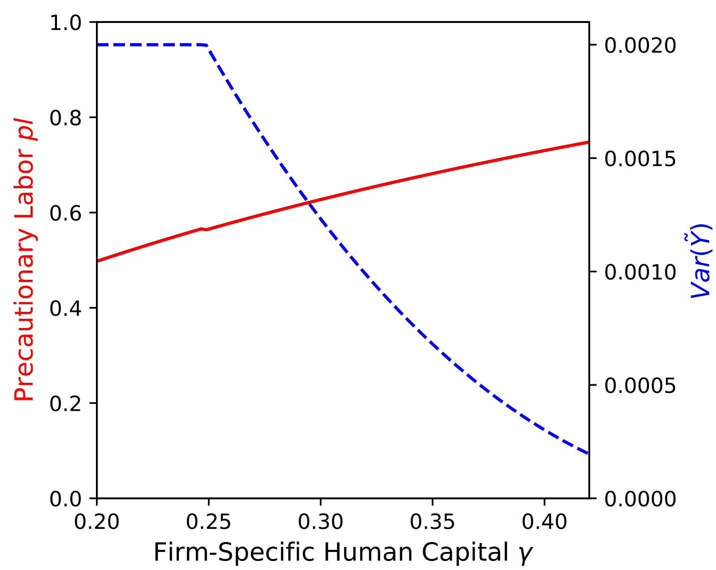
Figures

Figure 1: Model

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

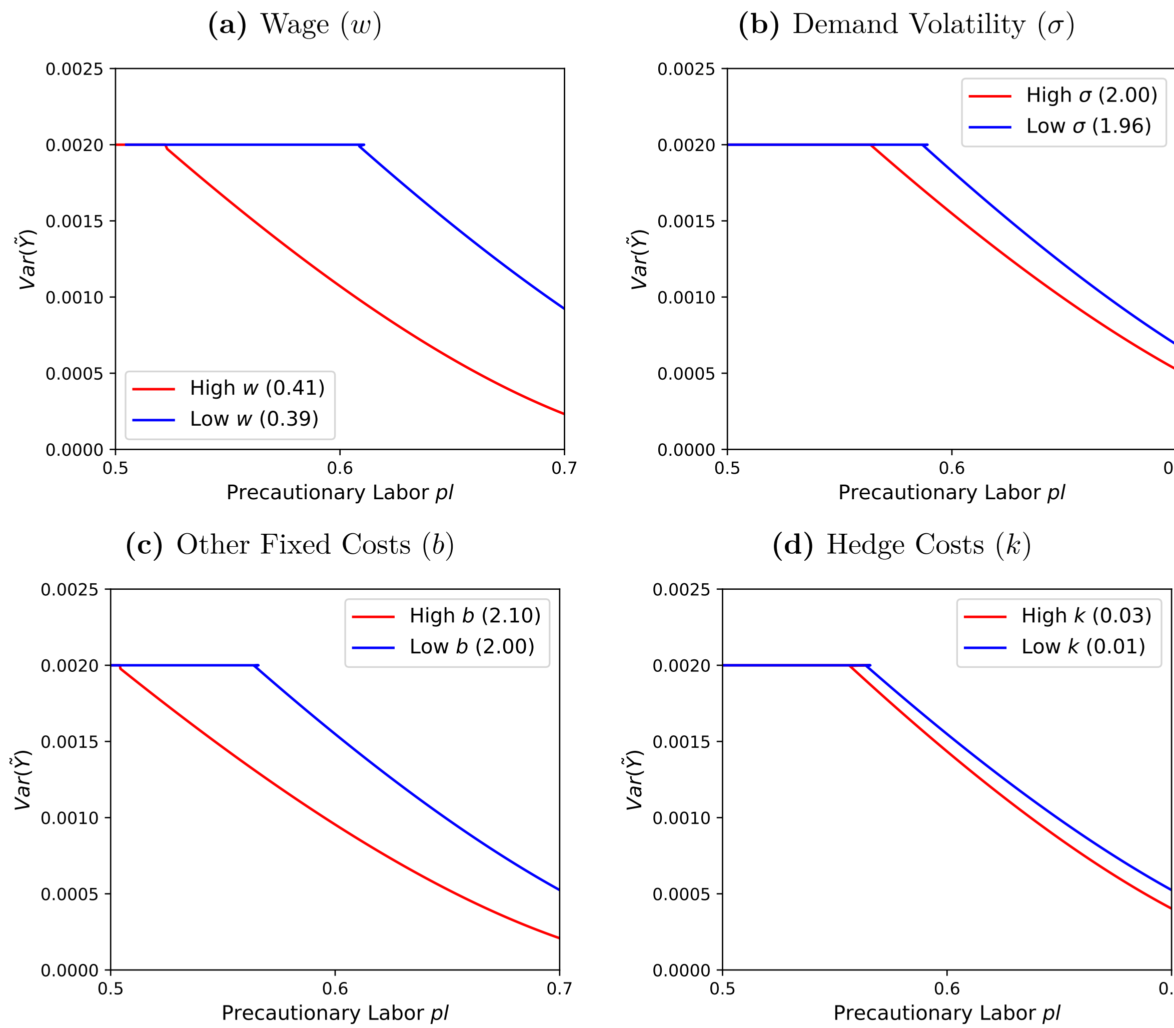


(b) Negative Comovement Across the Firm Distribution



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

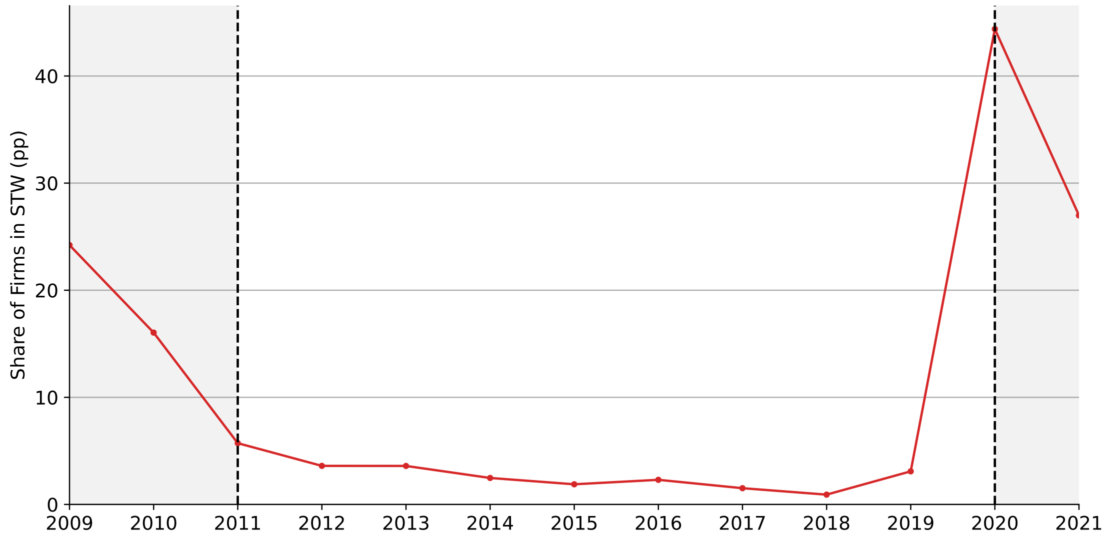
Figure 2: Model: Comparative Statics



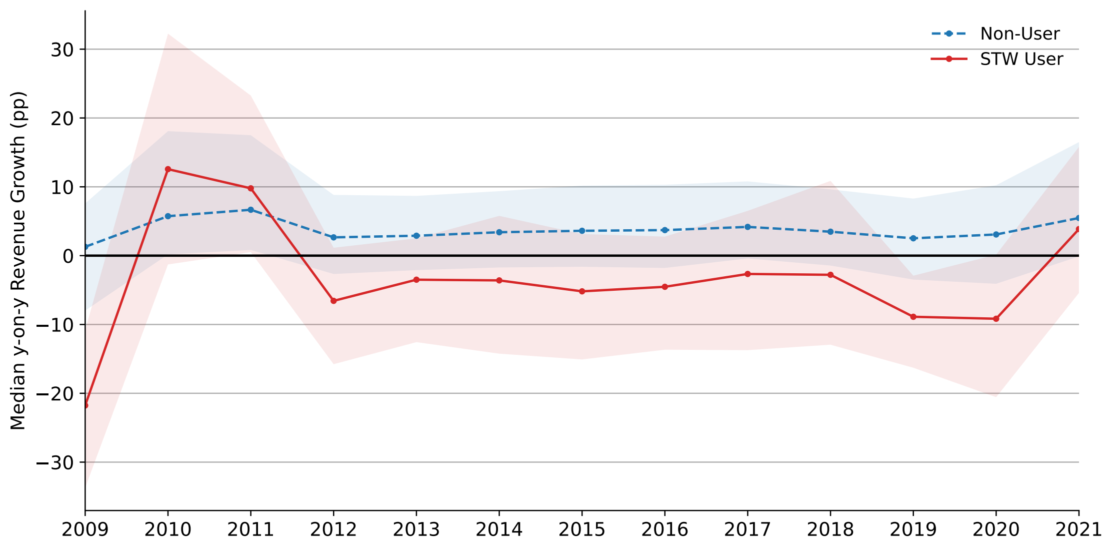
Notes: The figure shows comparative statics in w (Panel (a)), σ (Panel (b)), b (Panel (c)), and k (Panel (d)) of the optimal choice of precautionary labor (pl, x-axis) and the unhedged exchange-rate variance ($Var(\tilde{Y})$, y-axis). The baseline parameter specification is as before: $\mu = 10, \sigma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

Figure 3: STW Usage Over Time

(a) Usage Peaked During Eased-Access Episodes (Grey)

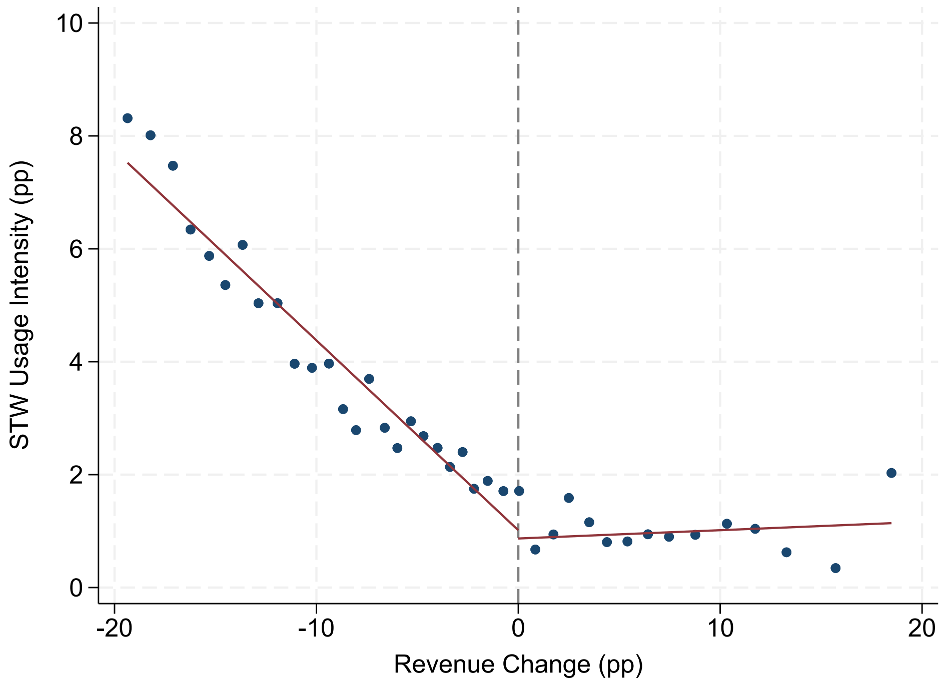


(b) Drop-and-Rebound Among Users Muted in 2020 Compared to 2009



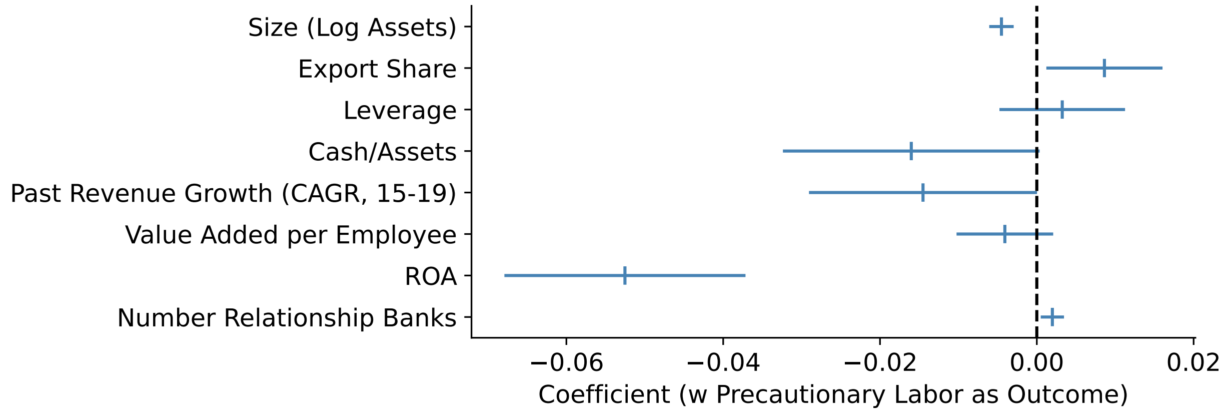
Notes: Panel (a) shows the per-year share of firms in STW from 2009 until 2021. The shaded areas indicate episodes of eased access to STW (2009-2011, since March 2020). Panel (b) shows the median year-on-year revenue growth in percentage points among users (solid red) and non-users (dashed blue), with status defined per year. 25th and 75th percentiles are depicted as shaded areas in red (users) and blue (non-users). The figure is based on all matched firms (no revenue restriction).

Figure 4: Measuring Precautionary Labor



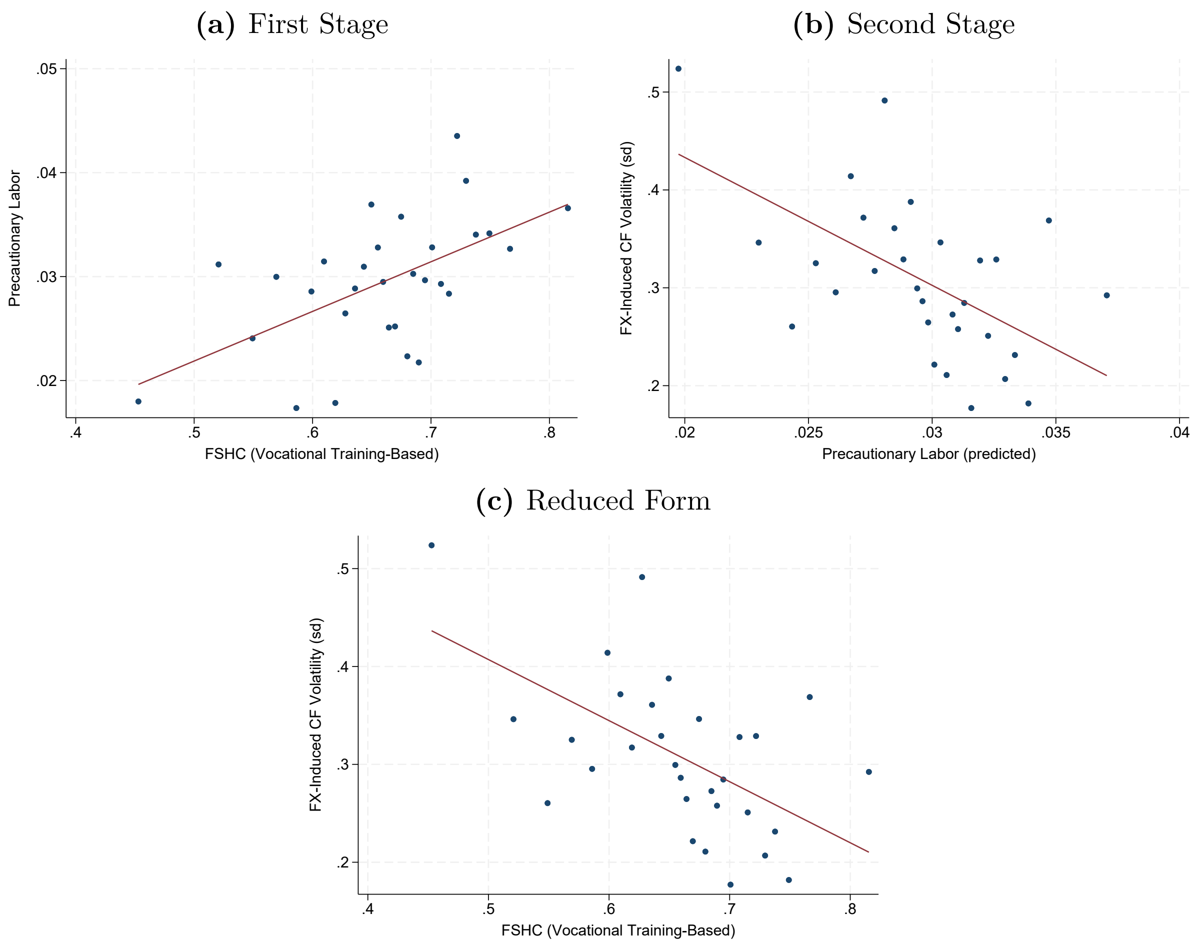
Notes: The figure shows a binned scatterplot of average STW usage intensity between June and December 2020 against the year-on-year revenue change 2020 (in pp). STW usage intensity is defined as the average monthly worker-equivalent of the reduction in work relative to employment (for details see section 4.3). We define *Precautionary Labor* as residual STW Usage Intensity after controlling for the change in revenue.

Figure 5: Who Holds Precautionary Labor?



Notes: The figure shows the estimated OLS coefficients and 95% confidence intervals of a regression of *Precautionary Labor* on firm characteristics (included one at a time). Industry-by-region FEs are included throughout, firm characteristics are as of 2019.

Figure 6: Effect of Precautionary Labor on FX-Induced CF Volatility



Notes: The figure shows binned scatterplots using the vocational-training-based instrument of the first stage in Panel (a), the second stage in Panel (b), and the reduced form in Panel (c) using the design (R3). The same set of controls is included as in the baseline specification (Table 5). For details on the construction of the measures *FX-induced CF Volatility* and *Precautionary Labor* see Section 6 and Section 4.3.

Tables

Table 1: Summary Statistics

	Mean	SD	p5	p50	p95	N Firms
Core Financial Information (2019)						
Assets (mil EUR)	190.047	1395.865	9.114	45.710	490.608	2310
Revenue (mil EUR)	187.617	636.136	15.691	73.112	620.768	2310
Employees	400.634	966.115	34.000	226.500	1182.000	2310
Leverage (pp)	59.328	31.729	16.122	59.004	97.761	2310
Cash/Assets (pp)	9.735	13.378	0.004	4.268	38.320	2310
ROA (pp)	7.507	13.585	-10.510	6.160	28.960	2310
Value Added per Employee (mil EUR)	0.132	0.478	0.044	0.091	0.267	1644
Firm-Level Employment Characteristics (2019)						
Avrg Age (years)	42.763	3.572	36.524	42.968	48.377	2310
Avrg Wage (EUR, daily, FT)	132.198	29.711	83.713	130.831	182.509	2310
Avrg Tenure (years)	10.506	4.270	4.067	10.169	18.099	2310
Shares by Occupation: Production	0.405	0.287	0.000	0.427	0.816	2310
Shares by Occupation: Service (IT, Scientific)	0.102	0.175	0.000	0.030	0.559	2310
Shares by Occupation: Service (Rest)	0.334	0.244	0.055	0.247	0.828	2310
FSHC (Vocational Training-Based)	0.659	0.107	0.432	0.687	0.788	2310
FSHC (Shortage Occupation-Based)	0.310	0.214	0.017	0.288	0.674	2310
Precautionary Labor Measures						
1(Precautionary Labor)	0.479	0.500	0.000	0.000	1.000	2309
Precautionary Labor (based on 2020)	0.029	0.053	0.000	0.000	0.134	2309
Precautionary Labor (based on 2009)	0.027	0.213	0.000	0.000	0.119	2237
Information on Exports and FX Volatility						
Export Share (2019)	0.443	0.279	0.012	0.459	0.900	2310
1(Exports to Outside Europe)	0.822	0.383	0.000	1.000	1.000	1192
Export Share Outside Europe (2019)	0.187	0.199	0.000	0.115	0.592	898
sd net gains (2010-2019)	0.308	0.584	0.002	0.114	1.263	2310
max net loss (2010-2019)	0.477	1.001	0.000	0.131	2.055	2310
1(FX Derivatives Use 2019)	0.265	0.442	0.000	0.000	1.000	2303
1(Active FX Management 2019)	0.191	0.394	0.000	0.000	1.000	2303
Number of Banks	2.609	1.385	1.000	2.000	5.000	2180

Notes: The table reports firm-level summary statistics for the core sample. For details on the precautionary-labor measures see Section 4.3, details on *FX-Induced CF Volatility* see Section 6 and details on the hedging information see Appendices B4 and B5.

Table 2: Individual-Level Short-Time-Work Receipt

	Dep Variable: STW Take-up					
	Full Sample	Users				
	Voc. Training (indiv)				Voc. Training (occup)	
	(1)	(2)	(3)	(4)	(5)	(6)
Vocational Training	0.081***	0.082***	0.048***	0.047***	0.019*	0.035***
	(0.001)	(0.001)	(0.008)	(0.006)	(0.011)	(0.011)
Month FEs	Yes	Yes	No	No	No	No
Firm x Month FEs	No	No	Yes	Yes	Yes	Yes
Basic Worker Controls	No	Yes	No	Yes	No	Yes
R^2	0.048	0.051	0.633	0.639	0.631	0.637
R^2 Adj.	0.048	0.051	0.631	0.637	0.629	0.636
N Firms	2,114	2,114	1,063	1,063	1,063	1,063
N Individuals	1,823,655	1,820,073	1,269,406	1,265,822	1,269,406	1,265,822

Notes: The table shows the results of a regression of STW receipt at the individual level on an individual-level vocational-training indicator (in columns 1-4) and the prevalence of vocational training in the occupation (in columns 5-6). Columns 3-6 are based on the firms and months with STW usage. Basic worker controls are included in columns 2, 4 and 6 and include gender, age group (younger than 35, 35-54, 55 and above) and wage tercile within the firm. The sample (cf. Table 1) excludes firms with incalculable individual-level STW information (see Section 3 for details).

Table 3: Comovement of Profitability with Industry-Wide Demand, by Precautionary Labor

	Dep. Variable:					
	ROA (Δ yoy)			CF (Δ yoy)		
	(1)	(2)	(3)	(4)	(5)	(6)
1(Precautionary Labor)	-0.080			-0.097***		
	(0.04)			(0.02)		
1(Precautionary Labor) × 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
R^2 Adj.	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 sample of matched firms with stable output window (see Panel (b) of Table D.1). *1(Precautionary Labor)* 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 4.3. Δ *Industry-Level Demand* is the year-on-year change in the ifo Business Climate index (6m-ahead expectations, provided by the ifo Institut) per sector as of March each year. Robust standard errors, clustered at the industry level, are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Precautionary Labor, Total and FX-Induced Cash-Flow Volatility

(a) Total vs. FX-Induced CF Volatility

	Dep. Variable: Cash Flow Volatility						
	Total					FX-Induced	
	sd	sd	sd	sd	sd	sd	max
1(Precautionary Labor)	0.076						
	(0.338)						
Log Assets 19	0.925***	0.933***	0.876***	0.846***	0.580**	0.046***	0.077***
	(0.152)	(0.153)	(0.153)	(0.187)	(0.276)	(0.014)	(0.020)
Revenue Change 19-20	-2.274	-1.786	-1.761	-2.780	1.216	-0.061	-0.079
	(1.753)	(1.763)	(1.758)	(2.091)	(1.926)	(0.158)	(0.269)
Precautionary Labor		4.004	1.732	3.339	-2.084	-0.430**	-0.748*
		(3.222)	(3.209)	(3.039)	(3.501)	(0.208)	(0.387)
ROA 19			-0.065***				
			(0.019)				
Value Added per Employee 19				1.512***			
				(0.244)			
Export Share					2.203**	0.445***	0.722***
					(0.899)	(0.053)	(0.094)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.099	0.099	0.107	0.141	0.154	0.105	0.094
R^2 Adj.	0.072	0.072	0.079	0.107	0.126	0.075	0.063
N Firms	6,456	6,456	6,456	4,840	2,274	2,274	2,274

(b) Adding Controls

	Dep Variable: FX-Induced CF Volatility							
	OLS		OLS		OLS		OLS	
	sd	max	sd	max	sd	max	sd	max
Precautionary Labor	-0.477**	-0.856**	-0.749**	-1.159*	-0.323	-0.791*	-0.439**	-0.659*
	(0.21)	(0.40)	(0.36)	(0.59)	(0.23)	(0.45)	(0.22)	(0.40)
Log Assets 19	0.045***	0.076***	0.069***	0.109***	0.030**	0.064**	0.049***	0.087***
	(0.01)	(0.02)	(0.03)	(0.04)	(0.01)	(0.03)	(0.01)	(0.02)
Export Share 19	0.445***	0.722***			0.468***	0.915***	0.433***	0.704***
	(0.05)	(0.09)			(0.08)	(0.15)	(0.05)	(0.10)
Revenue Change 19-20	-0.067	-0.095	-0.236	-0.338	0.260	0.389	-0.036	-0.021
	(0.16)	(0.27)	(0.26)	(0.46)	(0.20)	(0.40)	(0.17)	(0.28)
ROA 19	-0.001	-0.003						
	(0.00)	(0.00)						
Export Share Outside Europe 19			0.536***	0.737***				
			(0.12)	(0.19)				
Import Share					0.268***	0.354***		
					(0.07)	(0.13)		
N Relationship Banks							-0.016*	-0.041***
							(0.01)	(0.01)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.106	0.095	0.119	0.078	0.131	0.114	0.107	0.096
R^2 Adj.	0.075	0.064	0.064	0.020	0.086	0.067	0.074	0.063
N Firms	2,274	2,274	881	881	938	938	2,148	2,148

Notes: The table reports estimated OLS coefficients from specification (R2). In Panel (a), columns 1-5 use total CF volatility on the LHS, while columns 6 and 7 use FX-Induced CF Volatility on the LHS. Column 1 uses a binary variable that takes the value of 1 if a firm uses STW during the eased-access episode of 2020, while the other columns consider the continuous measure (cf. Section 4.3). In Panel (b), different control variables are added. 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 definition in Section 6).

Table 5: Instrumenting Precautionary Labor with Labor-Side Rigidities

(a) Outcome: Unhedged FX Exposure

	Dep. Variable: FX-Induced CF Volatility					
	OLS		2SLS		Reduced Form	
	sd	max	sd	max	sd	max
Precautionary Labor	-0.477**	-0.856**	-13.837**	-26.366***		
	(0.212)	(0.403)	(5.639)	(9.908)		
Log Assets 19	0.045***	0.076***	-0.022	-0.053	0.047***	0.077***
	(0.014)	(0.020)	(0.035)	(0.058)	(0.014)	(0.020)
Revenue Change 19-20	-0.067	-0.095	-2.549**	-4.833***	-0.026	-0.027
	(0.158)	(0.269)	(1.057)	(1.868)	(0.143)	(0.242)
Export Share 19	0.445***	0.722***	0.586***	0.991***	0.419***	0.672***
	(0.053)	(0.094)	(0.097)	(0.178)	(0.051)	(0.090)
ROA 19	-0.001	-0.003	-0.008**	-0.016***	-0.001	-0.002
	(0.001)	(0.002)	(0.003)	(0.006)	(0.001)	(0.002)
FSHC (Vocational Training-Based)					-0.628***	-1.202***
					(0.209)	(0.339)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Instrument 1st Stage			.045	.045		
Partial R^2 1st Stage			.004	.004		
AR 95% CI			[-32.05,-4.84]	[-59.91,-11.33]		
Kleibergen-Paap F-statistic			13.530	13.530		
N Firms	2,274	2,274	2,274	2,274	2,275	2,275

(b) Outcome: Usage of FX Derivatives

	Dep. Variable: FX Derivatives Use		
	OLS	2SLS	Reduced
Precautionary Labor	0.123	6.362**	
	(0.185)	(2.992)	
Log Assets 19	0.097***	0.129***	0.097***
	(0.008)	(0.017)	(0.008)
Revenue Change 19-20	0.246**	1.403**	0.244**
	(0.102)	(0.565)	(0.095)
Export Share 19	0.189***	0.122**	0.199***
	(0.035)	(0.052)	(0.035)
ROA 19	-0.001**	0.002	-0.001**
	(0.001)	(0.002)	(0.001)
FSHC (Vocational Training-Based)			0.283***
			(0.109)
Industry x Region FEs	Yes	Yes	Yes
Instrument 1st Stage		.045	
Partial R^2 1st Stage		.004	
AR 95% CI		[1.59, 16.26]	
Kleibergen-Paap F-statistic		12.872	
N Firms	2,268.000	2,268.000	2,269.000

Notes: The table reports the estimated coefficients from specification (R3) instrumenting *Precautionary Labor* with the vocational training-based instrument. Panel (a) uses unhedged FX-induced CF volatility as outcomes, while Panel (b) uses an indicator for whether firms use FX derivatives in 2019. In each panel, the first column(s) show the OLS, the following column(s) the 2SLS and the final column(s) the reduced form estimates. Two versions of the variable *FX-Induced CF Volatility* are considered: standard deviation of net FX gains to revenue (*sd*) and maximum of net FX losses to revenue (*max*) (see definition in Section 6). For details on the construction of *Precautionary Labor* see Section 4.3. Control variables are as of 2019. Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Robustness: Timing

(a) Occupational Composition Measured before FX Measurement Window

	Dep. Variable: FX-Induced CF Volatility					
	OLS		2SLS		Reduced Form	
	sd	max	sd	max	sd	max
Precautionary Labor	-0.608***	-0.879**	-21.488**	-34.931**		
	(0.232)	(0.392)	(9.286)	(14.039)		
Log Assets 13	0.047***	0.076***	-0.043	-0.070	0.049***	0.079***
	(0.015)	(0.023)	(0.045)	(0.068)	(0.015)	(0.023)
Revenue Change 19-20	-0.119	-0.153	-4.020**	-6.572**	-0.055	-0.074
	(0.171)	(0.258)	(1.744)	(2.654)	(0.153)	(0.229)
Export Share 19	0.521***	0.779***	0.726***	1.107***	0.485***	0.715***
	(0.059)	(0.092)	(0.138)	(0.217)	(0.057)	(0.088)
ROA 13	-0.004***	-0.004*	-0.005***	-0.006**	-0.004***	-0.004*
	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)
FSHC (Vocational Training-Based, 2013)					-0.983***	-1.677***
					(0.300)	(0.452)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Instrument 1st Stage			.048	.048		
Partial R^2 1st Stage			.005	.005		
AR 95% CI			[... ,-8.13]	[... ,-14.73]		
Kleibergen-Paap F-statistic			9.641	10.935		
N Firms	2,110	2,156	2,106	2,152	2,107	2,153

(b) Precautionary Labor based on the 2009 Eased-Access Episode

	Dep. Variable: FX-Induced CF Volatility					
	OLS		2SLS		Reduced Form	
	sd	max	sd	max	sd	max
Precautionary Labor (based on 2009)	-0.604**	-0.905**	-18.325*	-33.617*		
	(0.266)	(0.443)	(9.611)	(17.254)		
Log Assets 08	0.045***	0.084***	-0.023	-0.039	0.043***	0.082***
	(0.017)	(0.027)	(0.038)	(0.071)	(0.016)	(0.027)
Revenue Change 08-09	0.120	0.256**	-1.280*	-2.328*	0.139*	0.277**
	(0.079)	(0.115)	(0.738)	(1.335)	(0.072)	(0.111)
Export Share 19	0.484***	0.837***	0.763***	1.345***	0.456***	0.779***
	(0.061)	(0.119)	(0.164)	(0.307)	(0.059)	(0.116)
ROA 08	-0.002**	-0.004	-0.009**	-0.015**	-0.002**	-0.003
	(0.001)	(0.002)	(0.004)	(0.008)	(0.001)	(0.002)
FSHC (Vocational Training-Based, 2008)					-0.336***	-0.615***
					(0.121)	(0.198)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Instrument 1st Stage			.019	.019		
Partial R^2 1st Stage			.006	.006		
AR 95% CI			[... , -6.04]	[... ,-12.89]		
Kleibergen-Paap F-statistic			5.299	5.299		
N Firms	1,512	1,512	1,508	1,508	1,515	1,515

Notes: The table reports variants of the specification (R3) in terms of timing. In Panel (a) the instrument is constructed based on 2013 data while the measurement window for *FX-Induced CF Volatility* is shortened to 2014-2020 (cf. Section 6) with controls measured in 2013 (except for export share where this is infeasible). In Panel (b) *Precautionary Labor* is constructed based on STW usage during the eased-access episode in 2009. Control variables (except export share) as well as *Vocational Share* are as of 2008 (see Section 7.2 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 definition in Section 6). For details on the construction of *Precautionary Labor* see Section 4.3. Control variables are as of 2019. Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Including Both Instruments

	Dep. Variable: FX-Induced CF Volatility			
	2SLS: Shortage-Based		2SLS: Both	
	sd	max	sd	max
Precautionary Labor	-6.343**	-11.777**	-8.514***	-16.002***
	(2.562)	(4.646)	(2.693)	(5.024)
Log Assets 19	0.016	0.021	0.005	-0.001
	(0.018)	(0.031)	(0.020)	(0.034)
Revenue Change 19-20	-1.157**	-2.123**	-1.560***	-2.908***
	(0.520)	(0.921)	(0.532)	(0.980)
Export Share 19	0.507***	0.837***	0.530***	0.881***
	(0.062)	(0.111)	(0.067)	(0.123)
ROA 19	-0.004***	-0.009***	-0.005***	-0.011***
	(0.002)	(0.003)	(0.002)	(0.003)
Industry x Region FEs	Yes	Yes	Yes	Yes
AR 95% CI	[-13.02,-2.06]	[-23.89,-4.00]		
Effective F (MOP)	22.16	22.16	16.12	16.12
MOP 10% crit. val. (TSLS)	23.11	23.11	7.13	7.09
Overid. (Hansen J) p-value			0.14	0.07
N Firms	2,274	2,274	2,274	2,274

Notes: The table reports the estimated 2SLS coefficients from specification (R3) instrumenting *Precautionary Labor* with the shortage occupation-based instrument (columns 1 and 2) and with both instruments (columns 3 and 4). 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 definition in Section 6). For details on the construction of *Precautionary Labor* see Section 4.3. Control variables are as of 2019. Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Firm Characteristics by Hedging Status

(a) By FX Derivatives Usage

	No FX Derivatives					FX Derivatives					Diff means
	Mean	p10	p50	p90	N	Mean	p10	p50	p90	N	p-value
Core Financial Information (2019)											
Assets (mil EUR)	97.75	12.15	40.60	165.82	1692	442.39	22.51	78.35	594.08	611	0.00
Revenue (mil EUR)	124.36	19.83	63.54	222.24	1692	357.74	36.98	111.36	742.00	611	0.00
Employees	305.08	58.00	205.50	575.00	1692	662.08	49.00	289.00	1319.00	611	0.00
Leverage (pp)	59.48	22.98	58.01	93.07	1692	58.83	25.22	61.17	88.93	611	0.67
Cash/Assets (pp)	10.45	0.02	4.80	29.20	1692	7.80	0.04	3.14	22.55	611	0.00
ROA (pp)	7.99	-4.61	6.62	22.58	1692	6.16	-3.97	5.08	18.54	611	0.00
Value Added per Employee (mil EUR)	0.11	0.05	0.09	0.19	1183	0.18	0.06	0.10	0.20	456	0.01
Firm-Level Employment Characteristics (2019)											
Avrg Age (years)	42.83	38.03	43.15	47.34	1692	42.58	38.80	42.62	46.22	611	0.14
Avrg Wage (EUR, daily, FT)	131.45	92.24	129.71	172.33	1692	134.08	98.80	134.72	169.41	611	0.06
Avrg Tenure (years)	10.32	4.94	9.98	16.15	1692	11.00	5.84	10.83	16.33	611	0.00
Information on Exports and FX Volatility											
Export Share (2019)	0.42	0.05	0.41	0.81	1692	0.51	0.11	0.56	0.83	611	0.00
sd net gains	0.28	0.00	0.09	0.67	1692	0.39	0.02	0.20	0.93	611	0.00
max net loss	0.44	0.00	0.10	1.15	1692	0.57	0.01	0.22	1.38	611	0.00
Number of Banks	2.46	1.00	2.00	4.00	1592	3.02	1.00	3.00	5.00	581	0.00
1(Relationship Bank: Local)	0.52	0.00	1.00	1.00	1592	0.51	0.00	1.00	1.00	581	0.71
1(Relationship Bank: Grossbank)	0.84	0.00	1.00	1.00	1592	0.88	0.00	1.00	1.00	581	0.01

(b) Among Non-Users: By Operational FX Hedging

	No Active Hedging					Active Hedging					Diff means
	Mean	p10	p50	p90	N	Mean	p10	p50	p90	N	p-value
Core Financial Information (2019)											
Assets (mil EUR)	97.99	11.68	40.35	166.62	1386	96.66	14.95	42.74	163.24	306	0.95
Revenue (mil EUR)	123.26	19.36	63.50	221.38	1386	129.33	22.17	64.38	245.95	306	0.77
Employees	306.56	60.00	210.00	565.00	1386	298.35	46.00	188.50	578.00	306	0.75
Leverage (pp)	59.05	22.90	58.30	93.60	1386	61.41	23.98	57.64	91.29	306	0.28
Cash/Assets (pp)	10.27	0.02	4.63	28.49	1386	11.22	0.05	5.83	32.11	306	0.29
ROA (pp)	8.24	-4.61	6.59	24.10	1386	6.88	-4.67	6.76	19.36	306	0.14
Value Added per Employee (mil EUR)	0.11	0.05	0.09	0.19	970	0.13	0.05	0.09	0.19	213	0.02
Firm-Level Employment Characteristics (2019)											
Avrg Age (years)	42.82	38.01	43.10	47.36	1386	42.90	38.19	43.21	47.28	306	0.72
Avrg Wage (EUR, daily, FT)	130.49	91.00	128.75	169.96	1386	135.84	98.40	133.94	175.59	306	0.01
Avrg Tenure (years)	10.36	4.91	10.02	16.19	1386	10.15	4.94	9.91	16.04	306	0.43
Information on Exports and FX Volatility											
Export Share (2019)	0.40	0.04	0.39	0.80	1386	0.50	0.09	0.53	0.84	306	0.00
sd net gains	0.26	0.00	0.08	0.62	1386	0.36	0.01	0.15	0.85	306	0.01
max net loss	0.41	0.00	0.09	1.01	1386	0.58	0.00	0.16	1.42	306	0.00
Number of Banks	2.49	1.00	2.00	4.00	1303	2.35	1.00	2.00	4.00	289	0.10
1(Relationship Bank: Local)	0.53	0.00	1.00	1.00	1303	0.46	0.00	0.00	1.00	289	0.03
1(Relationship Bank: Grossbank)	0.84	0.00	1.00	1.00	1303	0.83	0.00	1.00	1.00	289	0.59

Notes: The table reports summary statistics depending on hedging status. Panel (a) splits the sample by derivatives usage in 2019. Panel (b) restricts attention to firms that do not use FX derivatives and instead uses the AI-assisted classification on whether the firm uses operational FX management strategies (for details see Appendix B5).

Appendix:

Do Firms Hedge Human Capital?

Christina Brinkmann, Stefanie Wolter

A Appendix: Model Proofs

A1 Proof of Lemma 1

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

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

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

Hence,

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

and

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

With E short-hand for the expected cashflow,

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

it follows that

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

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

□

A2 Proof of Proposition 1

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

Step 1: Preliminary properties.

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

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

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

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

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

Then the derivatives of E read

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

Note that

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

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

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

from assumptions A2 and A3. We know for $> \mu$ and below the unconstrained optimum c^* that

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

since from assumption A6, we have for all such c

$$(b + \gamma wc) < \frac{3}{5}\mu(1 - a - (1-\gamma)w) \tag{A22}$$

while for β_{1u}, the denominator of λ_u,

$$\begin{aligned}
\beta_{1u} = 1 - (1-\gamma)w - q - k(a-q) &\leq (1 - a - (1-\gamma)w) && \text{(A23)} \\
\Leftrightarrow (a-q)(1-k) &\geq 0, && \text{(A24)}
\end{aligned}$$

which holds. Hence the default probability takes the form

$$\begin{aligned}
P &:= P[CF_\gamma(c, q) < 0 | Y = (1-a)] && \text{(A25)} \\
&= P\left[\min(X, c) < \frac{\beta_2}{\beta_{1u}} \middle| Y = (1-a)\right] = F[\lambda_u]. && \text{(A26)}
\end{aligned}$$

Let

$$Q := f(\lambda_u)\lambda_u \tag{A27}$$

With

$$\partial_c \lambda_i = \lambda_i \frac{\gamma w}{\beta_2} \tag{A28}$$

$$\partial_q \lambda_i = (-\lambda_i^2) \frac{(k+\delta_i)}{\beta_2} \text{ with } \delta_i = \begin{cases} 1 & \text{for } i = o \\ 0 & \text{for } i = m \\ -1 & \text{for } i = u, \end{cases} \tag{A29}$$

then

$$\partial_q Q = \left[f'(\lambda_u)\lambda_u + f(\lambda_u) \right] (\partial_q \lambda_u) \qquad > 0 \tag{A30}$$

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

Subsequently

$$\partial_c P = f(\lambda_u)(\partial_c \lambda_u) = \frac{\gamma w}{\beta_2} Q \qquad > 0 \tag{A32}$$

$$\partial_q P = f(\lambda_u)(\partial_q \lambda_u) = \frac{(1-k)}{\beta_2} \lambda_u Q \qquad > 0. \tag{A33}$$

Note that

$$\partial_q Q = (\partial_q P) \Bigg[1 + \underbrace{\frac{\mu - \lambda_u}{\sigma} \frac{\lambda_u}{\sigma}}_{=:\tau} \Bigg] = (\partial_q P)(1+\tau) \tag{A34}$$

$$\partial_c Q = (\partial_c P)(1+\tau). \tag{A35}$$

With assumption A6 and subsequently $\lambda_u < \mu$ from (A21),

$$\partial_c^2 P = \frac{\gamma w}{\beta_2} \left(\partial_c Q - \frac{\gamma w}{\beta_2} Q \right) = \left(\frac{\gamma w}{\beta_2} \right)^2 f'(\lambda_u) \lambda_u^2 \qquad > 0 \tag{A36}$$

$$\partial_c \partial_q P = \frac{\gamma w}{\beta_2} (\partial_q Q) \qquad > 0 \tag{A37}$$

$$\partial_q^2 P = \frac{(1-k)}{\beta_2} \lambda_u \left(2f(\lambda_u) + f'(\lambda_u)\lambda_u \right) (\partial_q \lambda_u) \qquad > 0. \tag{A38}$$

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

$$(\partial_q \partial_c E)(\partial_q c^E) + \partial_c^2 E = 0 \;\Leftrightarrow\; \partial_q c^E = -\frac{\partial_c^2 E}{\partial_q \partial_c E} > 0, \tag{A39}$$

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

Step 3: There is a smooth function $c^P(q)$ that parameterizes $\{P = \alpha\}$ with $\partial_q c^P < 0$. Since $\partial_q P \neq 0$ by (A33), there is a smooth function, $c^P(q)$, that parameterizes $\{P = \alpha\}$. As above and using (A32) and (A33) for the inequality, it follows that

$$(\partial_q P)(\partial_q c^P) + \partial_c P = 0 \;\Leftrightarrow\; \partial_q c^P = -\frac{\partial_c P}{\partial_q P} < 0. \tag{A40}$$

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,

$$\mathcal{L} = E[CF] + \lambda \left(P[CF < 0] - t - \alpha\right), \tag{A41}$$

read for non-negative t

$$\begin{aligned} \partial_c E + \lambda \partial_c P &= 0 && \text{(A42)} \\ \partial_q E + \lambda \partial_q P &= 0 && \text{(A43)} \\ P[CF < 0] + t &= \alpha && \text{(A44)} \\ t\lambda &= 0. && \text{(A45)} \end{aligned}$$

For a binding constraint the optimality condition thus reads

$$\frac{\partial_c E}{\partial_q E} = \frac{\partial_c P}{\partial_q P}. \tag{A46}$$

Let

$$L := (\partial_c E)(\partial_q P) - (\partial_q E)(\partial_c P). \tag{A47}$$

Then we have $\partial_c E > 0$ on $\{L = 0\}$, since otherwise $L = (\partial_c E)(\partial_q P) - (\partial_q E)(\partial_c P) < 0$, contradiction. Hence, together with (A16), (A33), (A14), (A37), (A17), (A32), (A15) and (A36) we have

$$\partial_c L = \underbrace{(\partial_c^2 E)}_{<0} \underbrace{(\partial_q P)}_{>0} + \underbrace{(\partial_c E)}_{>0} \underbrace{(\partial_c \partial_q P)}_{>0} - \underbrace{(\partial_c \partial_q E)}_{>0} \underbrace{(\partial_c P)}_{>0} - \underbrace{(\partial_q E)}_{>0} \underbrace{(\partial_c^2 P)}_{>0} \tag{A48}$$

and, additionally with (A38) and (A18),

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

We first show

$$\partial_q L > 0 \qquad \text{on} \qquad \{L = 0\}. \tag{A50}$$

From (A49), it suffices to show

$$\begin{aligned} & (\partial_q E)(\partial_c \partial_q P) < (\partial_c E)(\partial_q^2 P) && \text{(A51)} \\ \overset{L=0}{\Leftrightarrow}\ & (\partial_c E)\frac{\partial_q P}{\partial_c P}(\partial_c \partial_q P) < (\partial_c E)(\partial_q^2 P) && \text{(A52)} \\ \Leftrightarrow\ & (\partial_q P)(\partial_c \partial_q P) < (\partial_c P)(\partial_q^2 P) && \text{(A53)} \\ \Leftrightarrow\ & \frac{\gamma w}{\beta_2} Q \frac{1-k}{\beta_2} \lambda_u \left[\lambda_u f'(\lambda_u) + f(\lambda_u)\right](\partial_q \lambda_u) < \frac{\gamma w}{\beta_2} Q \frac{1-k}{\beta_2} \lambda_u \left[\lambda_u f'(\lambda_u) + 2f(\lambda_u)\right](\partial_q \lambda_u) && \text{(A54)} \\ \Leftrightarrow\ & 0 < f(\lambda_u), && \text{(A55)} \end{aligned}$$

which is true.

We now show

$$\partial_c L < 0 \qquad \text{on} \qquad \{L = 0\}. \tag{A56}$$

From (A87) it suffices to show

$$\Big[(\partial_c E)(\partial_c \partial_q P) - (\partial_q E)(\partial_c^2 P) + (\partial_c^2 E)(\partial_q P)\Big] \frac{(\partial_c P)}{(\partial_c E)} < 0. \tag{A57}$$

Using $L = 0$, i.e., (A46), we have

$$(\partial_c E)(\partial_c \partial_q P) - (\partial_q E)(\partial_c^2 P) = \frac{(\partial_c E)}{(\partial_c P)} \Big[(\partial_c P)(\partial_c \partial_q P) - (\partial_q P)(\partial_c^2 P)\Big] \tag{A58}$$

$$= \frac{(\partial_c E)}{(\partial_c P)} \left(\frac{\gamma w}{\beta_2}\right)^2 \frac{1-k}{\beta_2} f(\lambda_u)^2 \lambda_u^3 \tag{A59}$$

and

$$(\partial_c^2 E)(\partial_q P) = \frac{(\partial_c E)}{(\partial_c P)} \frac{(\partial_c^2 E)}{\partial_c E} \left[(\partial_q P)(\partial_c P)\right] \tag{A60}$$

$$= \frac{(\partial_c E)}{(\partial_c P)} \frac{(-\beta_{1m}) f(c)}{\beta_{1m}(1 - F(c)) - \gamma w} f(\lambda_u) \lambda_u^2 f(\lambda_u) \lambda_u \left(\frac{\gamma w}{\beta_2}\right) \frac{1-k}{\beta_2} \tag{A61}$$

$$\leq (-1) \frac{(\partial_c E)}{(\partial_c P)} \frac{\gamma w}{\beta_2} \frac{1-k}{\beta_2} f(\lambda_u)^2 \lambda_u^3 \frac{f(c)}{(1 - F(c))}. \tag{A62}$$

Hence

$$\Big[(\partial_c E)(\partial_c \partial_q P) - (\partial_q E)(\partial_c^2 P) + (\partial_c^2 E)(\partial_q P)\Big] \frac{(\partial_c P)}{(\partial_c E)} \leq \frac{1-k}{\beta_2} \frac{\gamma w}{\beta_2} f(\lambda_u)^2 \lambda_u^3 \left[\frac{\gamma w}{\beta_2} - \frac{f(c)}{1 - F(c)}\right] \tag{A63}$$

$$< 0,$$

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

$$\left[\frac{\gamma w}{\beta_2} - \frac{f(c)}{1 - F(c)}\right] < 0 \Leftarrow \frac{f(\mu)}{1 - F(\mu)} \geq \frac{\gamma w}{\gamma w \mu + b} \tag{A64}$$

$$\Leftrightarrow \sqrt{\frac{2}{\pi}} \frac{1}{\sigma} \geq \frac{\gamma w}{\gamma w \mu + b} \tag{A65}$$

$$\Leftrightarrow b \geq \gamma w \left[\sqrt{\frac{\pi}{2}} \sigma - \mu\right], \tag{A66}$$

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 (A50) and (A56), we have

$$(\partial_q L)(\partial_q c^L) + \partial_c L = 0 \;\Leftrightarrow\; \partial_q c^L = -\frac{\partial_c L}{\partial_q L} > 0. \tag{A67}$$

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 3, 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).

□

A3 Proof of Proposition 2

For ease of notation, we omit the subscript for λ and take λ to be λ_u, and omit the subscript for β_1 and take $\beta_1 = \beta_{1m}$. As before in the proofs, we consider the amplitude of the partially hedged exchange rate $q := a - h$, instead of h. We consider the amplitude of the partially hedged exchange rate $q := a - h$, instead of h. The bound in assumption A5 is

$$\bar{k} := F^{-1}(\alpha)/\sigma(\sqrt{2/\pi} - 3/4)/(3 + F^{-1}(\alpha)/\sigma(\sqrt{2/\pi} - 3/4))$$

Step 1: Further preliminary properties.

We have

$$\partial_\gamma \partial_c E = (\partial_\gamma \beta_1)(1 - F(c)) - w = -wF(c) \qquad < 0 \tag{A68}$$

$$\partial_\gamma \partial_q E = k(\partial_\gamma E[\min(X, c)]) \qquad = 0. \tag{A69}$$

With

$$\partial_\gamma \lambda = \frac{w}{\beta_2}\lambda(c - \lambda). \tag{A70}$$

also

$$\partial_\gamma P = f(\lambda)(\partial_\gamma \lambda) = \frac{w}{\beta_2}(c - \lambda)Q \qquad > 0 \tag{A71}$$

$$\partial_\gamma \partial_q P = \frac{1-k}{\beta_2}\left[\partial_\gamma(\lambda Q) - \frac{wc}{\beta_2}(\lambda Q)\right] \tag{A72}$$

$$= \frac{1-k}{\beta_2}\left[\lambda(\partial_\gamma Q) - \frac{\lambda w}{\beta_2}(\lambda Q)\right] \tag{A73}$$

$$= \frac{1-k}{\beta_2}\left[\lambda(1+\tau)(\partial_\gamma P) - \underbrace{\frac{w}{\beta_2}(c-\lambda)Q}_{\partial_\gamma P}\lambda\frac{\lambda}{(c-\lambda)}\right] \tag{A74}$$

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

$$\partial_\gamma\partial_c P = \frac{w}{\beta_2}\left[\gamma\partial_\gamma Q + \left(1 - \frac{\gamma wc}{\beta_2}\right)Q\right] \tag{A76}$$

$$= \frac{w}{\beta_2}\left[\gamma(1+\tau) + \frac{b}{w}\frac{1}{(c-\lambda)}\right](\partial_\gamma P). \tag{A77}$$

Rearranging (A36) yields

$$\partial_c^2 P = \frac{\gamma w}{\beta_2}\left(\partial_c Q - \frac{\gamma w}{\beta_2}Q\right) \tag{A78}$$

$$= \frac{\gamma w}{\beta_2}(\partial_c P)(1+\tau) - \left(\frac{\gamma w}{\beta_2}\right)^2 Q \tag{A79}$$

$$= \frac{\gamma w}{\beta_2}(1+\tau)(\partial_q P)\frac{(\partial_c P)}{(\partial_q P)} - \frac{\gamma w}{\beta_2}(\partial_c P) \tag{A80}$$

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

We have

$$\partial_\gamma L = \underbrace{(\partial_\gamma\partial_c E)}_{<0}\underbrace{(\partial_q P)}_{>0} + \underbrace{(\partial_c E)}_{>0}(\partial_\gamma\partial_q P) - \underbrace{(\partial_\gamma\partial_q E)}_{=0}\underbrace{(\partial_c P)}_{>0} - \underbrace{(\partial_q E)}_{>0}\underbrace{(\partial_\gamma\partial_c P)}_{>0} \tag{A82}$$

$$= (\partial_\gamma\partial_c E)(\partial_q P) + Z \tag{A83}$$

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

$$G := \frac{1}{\lambda}\left[(\partial_c E)(1+\tau)\frac{\gamma w}{\beta_2}\lambda - k(1-F_c)\frac{\gamma w}{1-k} - (\partial_q E)\tau\frac{\gamma w}{\beta_2}\frac{\gamma w}{1-k}\right] \tag{A84}$$

and

$$H := k(1-F_c) - (\partial_c E)\frac{\lambda^2}{(c-\lambda)}\frac{(1-k)}{\beta_2} - (\partial_q E)\frac{\gamma w}{\beta_2}\left(1 + \frac{b}{\gamma w(c-\lambda)}\right). \tag{A85}$$

At the same time for $\partial_c L$, we have with (A87)

$$\partial_c L = (\partial_c^2 E)(\partial_q P) + N \tag{A86}$$

with

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

Hence,

$$\begin{aligned}
\partial_c L &= \left[(\partial_c^2 E) + G\right](\partial_q P) &\text{(A87)}\\
&=: \tilde{G}(\partial_q P). &\text{(A88)}
\end{aligned}$$

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

$$\partial_\gamma\partial_c E + (\partial_c^2 E)(\partial_\gamma c^E) = 0 \overset{\text{(A68),(A16)}}{\Rightarrow} \partial_\gamma c^E = -\frac{\partial_\gamma\partial_c E}{\partial_c^2 E} < 0. \tag{A89}$$

Likewise,

$$\partial_\gamma P + (\partial_c P)(\partial_\gamma c^P) = 0 \overset{\text{(A71),(A32)}}{\Rightarrow} \partial_\gamma c^P = -\frac{\partial_\gamma P}{\partial_c P} < 0. \tag{A90}$$

Likewise, from (A56) and (A50) we have

$$\partial_\gamma L + (\partial_c L)(\partial_\gamma c^L) = 0 \Leftrightarrow \partial_\gamma c^L = -\frac{\partial_\gamma L}{\partial_c L} < 0 \quad \text{on} \quad \{L=0\}. \tag{A91}$$

Step 3: $|\partial_\gamma c^L| < |\partial_\gamma c^P|$ and $|\partial_\gamma c^E| < |\partial_\gamma c^P|$.
From (A87) and (A83), we have

$$\begin{aligned}
\partial_\gamma L &= (\partial_\gamma\partial_c E)(\partial_q P) + Z &\text{(A92)}\\
&= (\partial_\gamma\partial_c E)(\partial_q P) + \left[\tilde{G}\lambda\frac{(1-k)}{\gamma w}\right](\partial_\gamma P) + H(\partial_\gamma P) - (\partial_c^2 E)\lambda\frac{(1-k)}{\gamma w}(\partial_\gamma P) &\text{(A93)}\\
&= \tilde{G}\frac{(\partial_q P)}{(\partial_c P)}(\partial_\gamma P) + H(\partial_\gamma P) + \underbrace{\left[(\partial_\gamma\partial_c E)\frac{\partial_q P}{\partial_\gamma P} - (\partial_c^2 E)\lambda\frac{(1-k)}{\gamma w}\right]}_{:=R}(\partial_\gamma P) &\text{(A94)}
\end{aligned}$$

$$= \partial_c L \frac{(\partial_\gamma P)}{(\partial_c P)} + (H + R)(\partial_\gamma P), \tag{A95}$$

with

$$R = (\partial_\gamma \partial_c E)\frac{\partial_q P}{\partial_\gamma P} - (\partial_c^2 E)\lambda \frac{(1-k)}{\gamma w} \tag{A96}$$

$$= (\partial_\gamma \partial_c E)\frac{\partial_q P}{\partial_\gamma P} - (\partial_c^2 E)\frac{\partial_q P}{\partial_c P}. \tag{A97}$$

Hence,

$$-\partial_\gamma c^L = \frac{\partial_\gamma L}{\partial_c L} = \frac{\partial_\gamma P}{\partial_c P} + \frac{(H+R)(\partial_\gamma P)}{(\partial_c L)} = -\partial_\gamma c^P + (H+R)\underbrace{\frac{(\partial_\gamma P)}{(\partial_c L)}}_{<0 \text{ on } \{L=0\}}, \tag{A98}$$

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

$$|\partial_\gamma c^L| < |\partial_\gamma c^P| \Leftrightarrow -\partial_\gamma c^L < -\partial_\gamma c^P \Leftrightarrow (H+R) > 0. \tag{A99}$$

Similarly,

$$-\partial_\gamma c^E = \frac{(\partial_\gamma \partial_c E)}{(\partial_c^2 E)} = \frac{\partial_\gamma P}{\partial_c P} + \frac{(\partial_c \partial_\gamma E) - (\partial_\gamma P)/(\partial_c P)(\partial_c^2 E)}{(\partial_c^2 E)} = -\partial_\gamma c^P + R\underbrace{\frac{(\partial_\gamma P)}{(\partial_c^2 E)(\partial_q P)}}_{<0}, \tag{A100}$$

and from step 2

$$|\partial_\gamma c^E| < |\partial_\gamma c^P| \Leftrightarrow -\partial_\gamma c^E < -\partial_\gamma c^P \Leftrightarrow R > 0. \tag{A101}$$

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

Claim: $R > 0$.

Proof of claim.

$$R = (\partial_\gamma \partial_c E)\frac{\partial_q P}{\partial_\gamma P} - (\partial_c^2 E)\frac{\partial_q P}{\partial_c P} \tag{A102}$$

$$= -F_c(1-k)\frac{\lambda}{(c-\lambda)} + \beta_1 f_c \frac{(1-k)}{\gamma w}\lambda \tag{A103}$$

$$= \frac{(1-k)\lambda}{(1-F_c)}\Big[-\frac{F_c(1-F_c)}{(c-\lambda)} + \underbrace{\frac{\beta_1}{\gamma w}(1-F_c)}_{>1 \text{ since } \partial_c E > 0} f_c\Big] \tag{A104}$$

$$\geq \frac{(1-k)\lambda}{(1-F_c)}\Big[-\frac{1}{4(c-\lambda)} + f_c\Big] \tag{A105}$$

From assumption A6 and subsequently (A21), as well as assumptions A2 and A1, we have

$$(c-\lambda) > c - \frac{3}{5}\mu > \frac{2}{5}\mu > 2\sigma. \tag{A106}$$

From assumption A3, we know $c < \mu + (5/4)\sigma$, hence $f_c > 1/(8\sigma)$. Plugged into (A105), this yields $R > 0$.

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

Proof of claim. From assumption A6 and subsequently (A21), we have $(c-\lambda)>(1/3)c$, hence

$$1+\frac{b}{\gamma w(c-\lambda)}\leq\frac{\gamma w+3b/c}{\gamma w}\leq\frac{3\beta_2/c}{\gamma w}. \tag{A107}$$

Thus, we have

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

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

$$\frac{f_\mu}{(1-F_\mu)}=\sqrt{\frac{2}{\pi}}\frac{1}{\sigma}\approx 0.79\frac{1}{\sigma}\geq\frac{3}{4}\frac{1}{\sigma}, \tag{A108}$$

the expression in brackets is positive if

$$\frac{\lambda}{(c-\lambda)}\frac{1}{\beta_2}(\beta_1-\gamma w)\leq\frac{3}{4}\frac{1}{\sigma} \tag{A109}$$

$$\Leftrightarrow\frac{(\beta_1-\gamma w)}{(\beta_1-q)}\frac{4}{3}\sigma\leq(c-\lambda). \tag{A110}$$

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

$$\frac{(\beta_1-\gamma w)}{(\beta_1-q)}\frac{4}{3}\leq 2\Leftrightarrow\frac{q}{w}-\gamma\leq\frac{(\beta_1-\gamma w)}{3w}, \tag{A111}$$

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

$$a\leq\frac{4}{9}(1-w)-\frac{1}{3}kh_{max} \tag{A112}$$

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

$$\Rightarrow\bar{\gamma}_{\min}\geq\frac{a}{w}-\frac{(\beta_1-\gamma w)}{3w}. \tag{A114}$$

From (A108), 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

$$\mathbb{D} := \Big\{(\gamma, q, c) | \gamma \in [\gamma_{min}, \gamma_{max}], q \in [q_{min}, a], c \in \mathbb{R}^+\Big\} =: \mathbb{D}_1 \times \mathbb{D}_2 \times \mathbb{D}_3 \tag{A115}$$

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

$$\mathbb{C}^{LP} := \{L = 0\} \cap \{P = \alpha\}. \tag{A116}$$

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

$$rank \begin{pmatrix} DL \\ DP \end{pmatrix} = 2. \tag{A117}$$

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

$$\det \begin{pmatrix} \partial_c L & \partial_q L \\ \partial_c P & \partial_q P \end{pmatrix} = (\partial_c L)(\partial_q P) - (\partial_q L)(\partial_c P) < 0. \tag{A118}$$

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

$$\{\gamma_{min}, \gamma_{max}\} \times \mathbb{D}_2 \times \mathbb{D}_3 \quad \cup \quad \mathbb{D}_1 \times \{q_{min}, a\} \times \mathbb{D}_3. \tag{A119}$$

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 $\{\gamma_1\} \times \mathbb{D}_2 \times \mathbb{D}_3$ 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 $\{\gamma_2 = \gamma_1 + \varepsilon\} \times \mathbb{D}_2 \times \mathbb{D}_3$ at the previous level of q, $q^{LP}(\gamma_1)$. Then,

$$\begin{aligned} c^P(\gamma_2, q^{LP}(\gamma_1)) \approx c^P(\gamma_1, q^{LP}(\gamma_1)) + \varepsilon \partial_\gamma c^P &= c^L(\gamma_1, q^{LP}(\gamma_1)) + \varepsilon \partial_\gamma c^P \\ &< c^L(\gamma_1, q^{LP}(\gamma_1)) + \varepsilon \partial_\gamma c^L \approx c^L(\gamma_2, q^{LP}(\gamma_1)), \end{aligned} \tag{A120}$$

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

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

B Appendix: Data Appendix

B1 Cleaning BTR-KuG

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

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

B2 Cleaning Dafne

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

Similar to the standard data cleaning methodology for ORBIS (Kalemli-Özcan, Sørensen, Villegas-Sanchez, Volosovych, and Yeşiltaş, 2024), we discard firms that do not pass basic data consistency checks on their key financials (whenever assets are available they are positive, equity exceeds assets in 2019 and 2020, fixed assets are never negative, revenues are never negative, sales-to-asset ratio is below the 99.9 percentile (pooled across all years), assets to not exceed those of VW, fixed asset-to-asset ratio below 1) *(17,200).* We demand that information on cash flow, cash and equity is available in 2019 *(16,400).*

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

B3 Details on the Relative Wage Bill Gapin BTRKUG

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

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

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

Firms are required to include information on their risk management in the appendix of annual reports, and we conduct a text analysis to identify mentions of FX hedging instruments. The reports are in German. We have manually downloaded annual reports for 28,495 firm-year observations, here we use the 2019 only.

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

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

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

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

	Pattern 1		Pattern 2	
	Percent	N	Percent	N
No mention	80.44%	3,709	87.73%	4,045
Only negated mentions	0.74%	34	1.00%	46
Sentences with mentions all conditional	0.33%	15	0.72%	33
Partially negated mentions	1.08%	50	0.26%	12
Hedges	17.41%	803	10.30%	475
Sum	100%	4,611	100%	4,611

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

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

B5 AI-based Classification of FX Risk-Management Strategies and Export Share (Firms' Reports)

We have manually downloaded annual reports for 4,613 firms in 2019 and extract the appendix of each annual report. We use ChatGPT (batch; gpt-5.4-nano; April 21, 2026) with the following prompt (original in German; translated) for each annual report:

> Analyze the complete annual report of a German firm. Use only statements from the text; no external knowledge, no speculation. Assess three fields: *exposition* (is the firm exposed to currency risk?), *financial_hedging* (does it use financial instruments to hedge currency risk?), and *operational_hedging* (does it use operational measures to manage currency risk?).
>
> **Answer logic.** "Yes" = explicitly/clearly documented; "No" = explicitly/clearly denied; "No Info" = not sufficiently clear. In case of contradictions, be conservative (⇒ "No Info").
>
> **exposition.** "Yes" if a currency/exchange-rate/foreign-currency risk is explicitly named, or a risk from foreign-currency transactions, receivables, liabilities, revenues, costs, financing, or cash flows is clearly described. "No" only if the firm clearly states that no (material) currency risks exist; otherwise "No Info." Foreign business, exports/imports, international markets, or foreign currencies without a clear risk reference are not sufficient, nor are general accounting principles (e.g., how foreign-currency assets are translated).
>
> **financial_hedging.** "Yes" only if currency-related financial hedging instruments are explicitly named (FX forwards, FX options, FX swaps, currency swaps, or other derivatives/hedges against currency risk). "No" if such instruments are explicitly denied—the explicit denial of FX forwards suffices, absent other positive evidence; otherwise "No Info." General statements about accounting, derivatives, hedging, risk management, foreign-currency loans, or financing do not qualify without a clear currency reference.
>
> **operational_hedging.** "Yes" only if operational measures with a clear currency reference are named (invoicing in euros, natural hedging, operational hedging at group level, price-hedging agreements, matching receipts and payments in the same currency, relocating procurement/production to reduce currency risk). "No" if such measures are explicitly denied; a statement that exchange-rate fluctuations are absorbed locally or not actively managed also counts as "No," absent positive evidence; otherwise "No Info." General purchasing, sales, production, or location strategies without a clear currency reference do not qualify.
>
> **Quotes.** Verbatim, short, relevant passages only (no paraphrases); max. 3 per field; max. 2 sentences (≈50 words) each; a quote may support only its own field; use `[]` if no evidence. "Yes"/"No" each require a directly supporting positive/negative quote; a negative quote may never yield "Yes." Keep *reasoning* short and close to the text.
>
> **Output.** Reply for each object with `{"reasoning":...,"answer":...,"zitate":[]}`. Permitted `answer` values: "Yes", "No", "No Info".

The following table compares the data to the key-word-based measure, while a manual comparison of the divergent cases suggested more accuracy of the AI-based classification.

	AI: FX Financial Hedging		
Keyword-based	Non-user	User	Total
Non-user	3,181	140	3,321
User	145	818	963
Total	3,326	958	4,284

We proceed similarly to extract the 2019 export share and 2019 export share outside Europe. We do so because the export-share information provided by Creditreform is not time-varying (and thus as of 2022) and potentially self-reported. We use ChatGPT (batch; gpt-5.4-nano; April 21, 2026) with the following prompt (original in German; translated):

> Analyze the complete annual report of a German firm. Use only statements from the text provided; no external knowledge, no speculation. Assess: *export_binary* (does the firm export abroad?); and, only if stated directly in the text (otherwise `null`): *sales_domestic* (domestic/Germany revenue, absolute), *sales_total* (total revenue, absolute with unit), *share_domestic* (domestic revenue share, as a percentage, e.g. "62%"), *sales_eu* (revenue in Europe excluding Germany, absolute with unit), *sales_noneu* (revenue outside Europe, absolute with unit), *share_noneu* (non-European revenue share, as a percentage), and *export_split* (the geographic revenue breakdown, e.g. by regions, countries, or domestic/foreign).
>
> **export_binary.** "Yes" = directly and explicitly documented; "No" = directly and explicitly denied; "No Info" = not sufficiently or clearly documented.
>
> **Numeric fields** (*sales_domestic*, *sales_total*, *share_domestic*, *sales_eu*, *sales_noneu*). Provide a value only if directly named in the text, otherwise `null`; statements from running text and tables are permitted, but indirect hints are not. Copy absolute numbers in the currency and notation used in the text, and percentages exactly as stated.
>
> **export_split.** Provide only directly named geographic revenue splits, otherwise `[]`; output as a list of the categories/regions/countries/ segments in their original wording from the text.
>
> **Quotes.** Verbatim, short, relevant passages only (no paraphrases); max. 3 per field; max. 2 sentences (≈50 words) each; use `[]` if no evidence. **Reasoning** very short and close to the evidence; no speculation or derivation from indirect hints; if no direct evidence exists, say so explicitly.
>
> **Output.** Reply for each object with {`"reasoning":...,"answer":...,"zitate":[]`}. Permitted `export_binary.answer`: "Yes"/"No"/"No Info"; numeric-field `answer`: string or `null`; `export_split.answer`: list of strings or `[]`.

As a consistency check, we also extract total sales (rf prompt) and compare this info to the sales information in Dafne. Whenever the readout was successful (for 95% of firms), they differ by at most 1% in 92% of cases.

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

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

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

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

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

B7 An Example of *FX Gains* and *FX Losses*

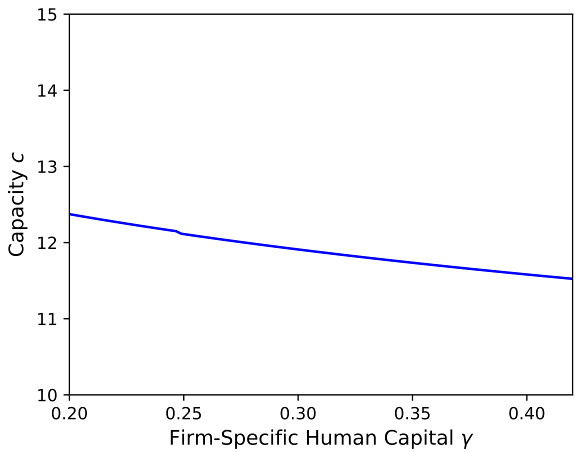
Consider a firm that produces in Europe and exports to the US. The firm invoices and ships goods on March 1 at a price of $1 mil, with payment due three months later on June 1. At the time of invoicing, €1 is worth $1.05, so the firm records 1/1.05 mil EUR on March 1. Suppose the euro appreciates and the exchange rate moves to \$1.15 per EUR by the settlement date. At settlement, 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 $\approx$ 83,000 EUR. If the firm conducts multiple such transactions throughout the year, it collects the corresponding revaluations in the variables *FX Gains* and *FX Losses*.

Now suppose the firm 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, and no net revaluation effect is expected: 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 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 the two methods imply different values for *FX Gains* and *FX Losses* separately, both yield the same net FX gains. Because our measures are built from variables booked after the hedge revalues, they reflect residual FX risk—consistent with the model.

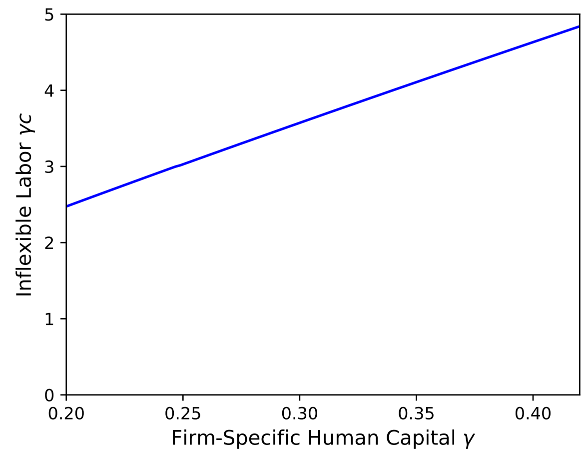
C Supplementary Figures

Figure C.1: Model: Further Illustrations

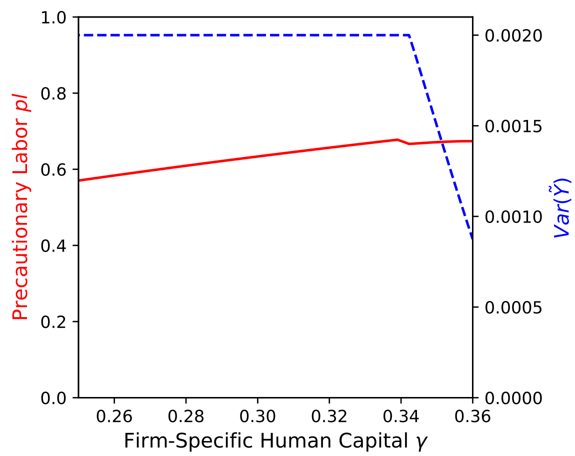
(a) Capacity c



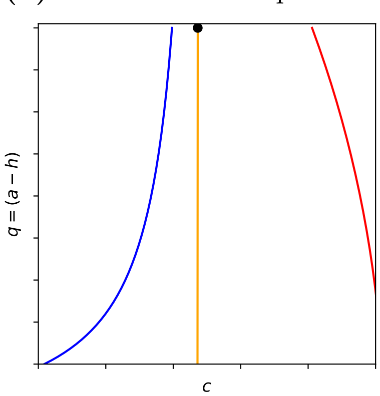
(b) Inflexible Labor γc



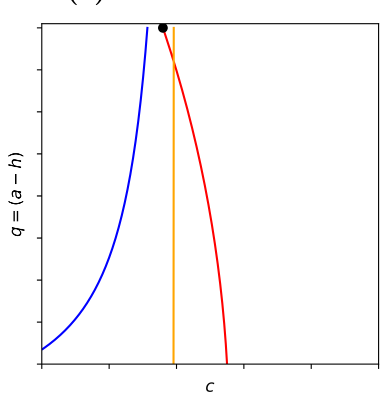
(c) Solution w Alternative Constraint



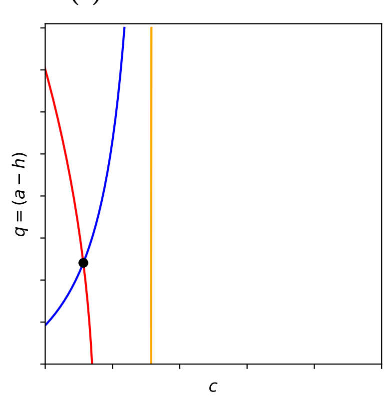
(d) Unconstrained Optimum



(e) Corner Solution

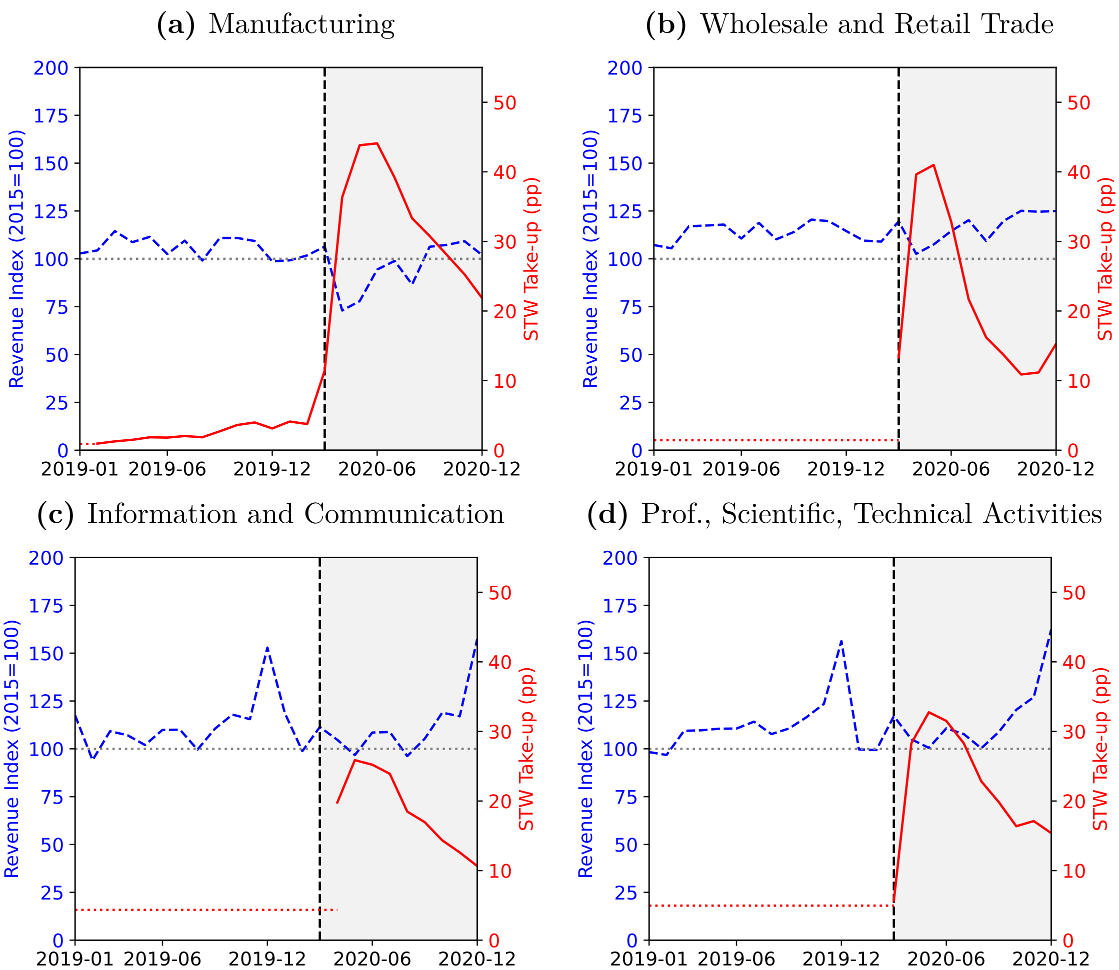


(f) Interior Solution



Notes: Panels (a) and (b) show how optimal *capacity*, c, and *inflexible labor*, γc, change as a function of firm-specific human capital γ, using the same specification as in Panel (b) of Figure 1. Panel (c) solves the model for the alternative constraint $P[CF < 0] < \alpha$ and following set of parameters: $\mu = 10, \sigma = 2, b = 2, a = 0.1, p = 0.1, w = 0.4, \alpha = 0.006, k = 0.005, q_{min} = 0.02$. The remaining panels illustrate the model solution (black dot) for increasing levels of γ. Panels (d), (e) and (f) correspond to cases a), b) and c) in Proposition 1, respectively. On the x-axis the *capacity*, c, and on the y-axis the amplitude of the exchange rate after hedging, $q = (a-h)$, are depicted. In each panel, the blue line corresponds to points on which the Lagrange optimality is satisfied, the yellow line to unconstrained optimal capacity choices for given levels of q, and the red line to points on which the constraint binds.

Figure C.2: STW Usage by Industry (Eased-Access Episodes in gray)



(a) Manufacturing

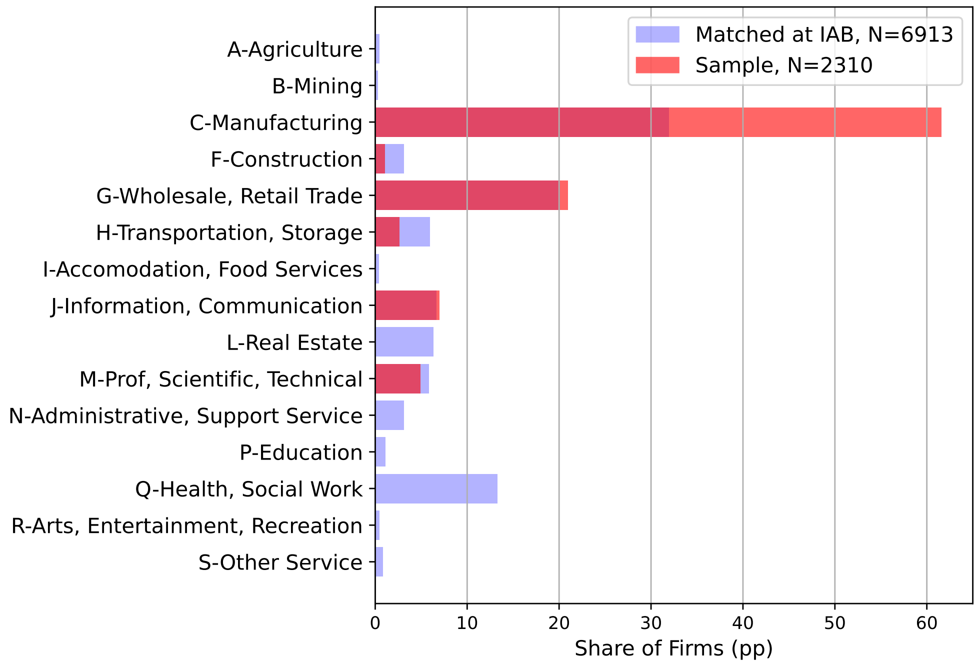
(b) Wholesale and Retail Trade

(c) Information and Communication

(d) Prof., Scientific, Technical Activities

Notes: Panels (a)-(d) plot monthly industry-wide revenue (blue, LHS scale) against the share of firms in STW per industry (red, RHS scale) for the four largest industries. Revenue is a value index, normalized to 100 in 2015 (raw series), from the Federal Statistical Office (tables 42152-0001, 45212-0005 and 47414-0005). Gaps in the data come from data protection (fewer than 20 firms, line below which no data is available shown in dotted red). Shaded areas indicate episodes of eased access to STW (2009-2011, since March 2020). The results are based on the sample of matched firms with stable output window (see Panel (b) of Table D.1).

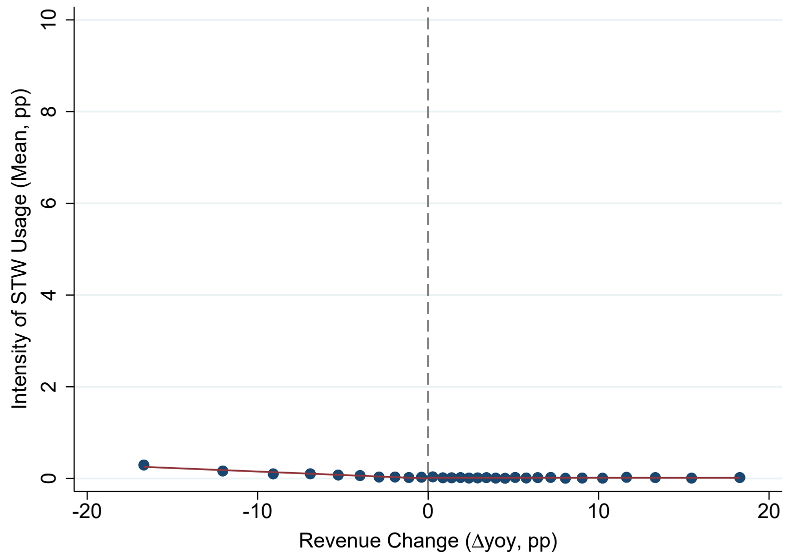
Figure C.3: Industry Composition



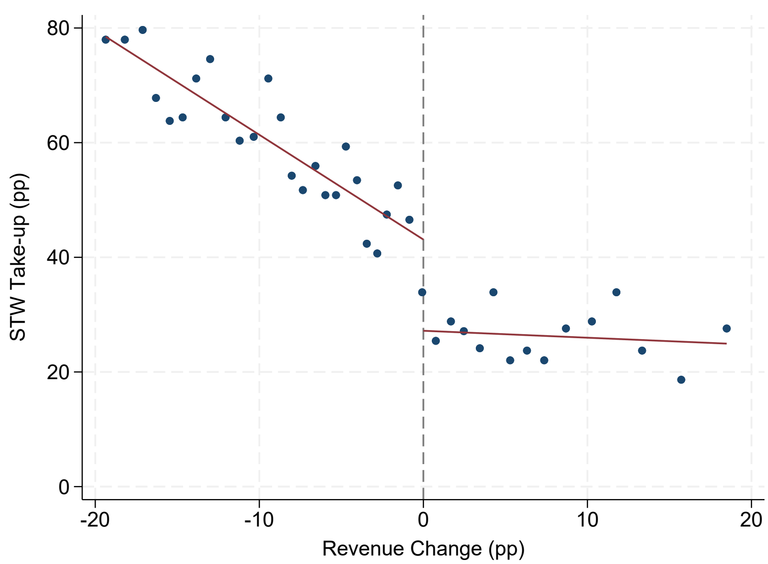
Notes: The figure shows the industry composition of the matched sample (cf. Panel (b) of Appendix Table D.1) and the final sample (cf. Table 1).

Figure C.4: Measure: Placebo and Binary Outcome

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

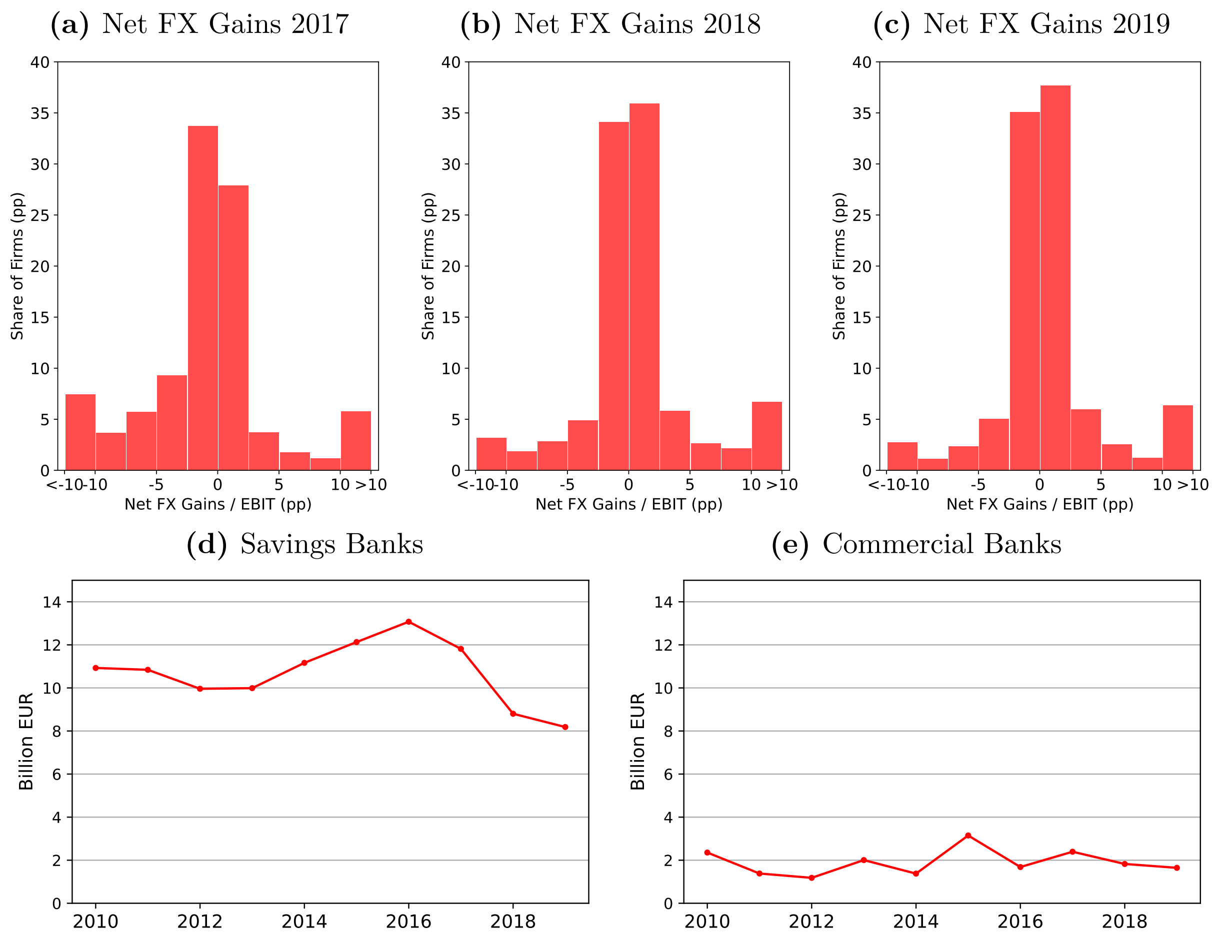


(b) STW Usage 2020 (Binary)



Notes: Panel (a) shows a replication of Figure 4 outside an eased-access episode. The sample consists of pooled firm-year observations for the years 2012-2019. The annual *Intensity of STW Usage* in a given year is defined analogously to before (cf. section 4.3) based on all months per year. On the x-axis is the annual year-on-year change in revenue (in pp). Panel (b) replicates Figure 4 using *1(Precautionary Labor)* as outcome. *1(Precautionary Labor)* 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 4.3.

Figure C.5: Relevance of FX Risk



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

D Supplementary Tables

Table D.1: Reference Summary Statistics

(a) All German Firms with Revenue Info

	Mean	SD	p5	p50	p95	N Firms
Core Financial Information (2019)						
Assets (mil EUR)	160.393	1877.862	0.763	28.306	384.119	16323
Revenue (mil EUR)	152.115	1426.667	1.355	38.427	379.815	16323
Employees	385.337	1616.889	18.000	145.000	1270.000	15709
Leverage (pp)	63.787	64.093	14.896	61.041	99.982	16323
Cash/Assets (pp)	13.246	17.877	0.009	5.795	52.968	16323
ROA (pp)	4.939	26.419	-17.150	4.020	30.220	16323
Value Added per Employee (mil EUR)	0.130	0.775	0.027	0.078	0.322	10820
Information on Exports and FX Volatility						
Export Share	0.382	0.292	0.010	0.340	0.900	6250
sd net gains (2010-2019)	0.365	0.733	0.002	0.119	1.487	4421
max net loss (2010-2019)	0.554	1.185	0.000	0.142	2.579	4421

(b) Matched Firms at IAB with Stable Output Window

	Mean	SD	p5	p50	p95	N Firms
Core Financial Information (2019)						
Assets (mil EUR)	160.393	2435.800	2.049	31.206	362.253	6913
Revenue (mil EUR)	139.312	1180.835	3.717	45.918	360.113	6913
Employees	351.919	1535.582	22.000	165.000	1123.000	6913
Leverage (pp)	59.091	40.897	15.196	58.348	98.241	6913
Cash/Assets (pp)	12.124	16.090	0.011	5.568	47.013	6913
ROA (pp)	6.474	15.908	-10.470	4.330	28.100	6913
Value Added per Employee (mil EUR)	0.129	0.866	0.036	0.081	0.307	5104
Firm-Level Employment Characteristics (2019)						
Avrg Age (years)	43.201	4.002	36.406	43.309	49.571	6913
Avrg Wage (EUR, daily, FT)	117.721	34.203	63.431	115.821	177.833	6913
Avrg Tenure (years)	9.692	4.083	3.718	9.320	16.896	6913
Shares by Occupation: Production	0.286	0.289	0.000	0.163	0.806	6913
Shares by Occupation: Service (IT, Scientific)	0.073	0.161	0.000	0.012	0.487	6913
Shares by Occupation: Service (Rest)	0.485	0.320	0.052	0.440	0.964	6913

Notes: The table reports firm-level summary statistics of two benchmark samples. Panel (a) uses all firms in Germany that report revenue information in 2019 while Panel (b) uses the sample of firms with a stable output window that can be matched to IAB data (see Section 3 for details).

Table D.2: Robustness: Comovement Using Industry-Wide Order Changes

(a) Industry-Wide Order Changes

	Dep. Variable:					
	ROA (Δ yoy)			CF (Δ yoy)		
	(1)	(2)	(3)	(4)	(5)	(6)
1(Precautionary Labor)	-0.044			-0.132***		
	(0.05)			(0.04)		
1(Precautionary Labor) × 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
R^2 Adj.	0.001	-0.003	-0.010	0.005	0.018	-0.010
N Observations	11,734	11,718	10,502	11,702	11,686	10,474

(b) Summary Statistics

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

Notes: Panel (a) reports the results of regression (R1) in a firm-year panel from 2010-2020. The results are based on the sample of matched firms with stable output window (see Panel (b) of Table D.1). Attention is restricted to manufacturing firms due to data availability of orders. *1(Precautionary Labor)* 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 4.3. Robust standard errors, clustered at the industry level, are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel (b) provides summary statistics for the panel analyses in Table 3 and Panel (a). Δ *Industry-Level Demand* is the year-on-year change in the ifo Business Climate index (6m-ahead expectations, provided by the ifo Institut) per sector as of March each year. Δ *Industry-Level Orders* is the relative year-on-year change in industry-level orders as of March each year. It is a value index, normalized to 100 in 2015 (raw series), from the Federal Statistical Office of Germany (tables 42151-0002). *Upturns* is a count of observations with a positive change in either measure.

Table D.3: Heterogeneity Along the Model Comparative Statics

	Dep. Variable: FX-Induced CF Volatility							
Heterogeneity Dimension:	Low Labor Share		Low Order Volatility		Low Leverage		More Than 3 Banks	
	sd	max	sd	max	sd	max	sd	max
Precautionary Labor	-1.115***	-1.860***	-0.786**	-1.036*	-0.516	-1.150*	-0.920***	-1.801***
	(0.303)	(0.500)	(0.351)	(0.594)	(0.379)	(0.652)	(0.302)	(0.512)
Heterogeneity Dimension × Precautionary Labor	1.020**	1.216*	1.376***	1.512	-0.266	-0.297	0.788*	1.832***
	(0.417)	(0.645)	(0.527)	(0.926)	(0.438)	(0.703)	(0.449)	(0.675)
Heterogeneity Dimension	-0.063*	-0.107*	-0.138***	-0.098	0.002	-0.023	-0.096**	-0.213***
	(0.038)	(0.062)	(0.051)	(0.091)	(0.041)	(0.067)	(0.038)	(0.057)
Log Assets 19	0.050**	0.086***	0.007	0.014	0.050**	0.085***	0.053**	0.098***
	(0.020)	(0.028)	(0.028)	(0.049)	(0.020)	(0.028)	(0.021)	(0.030)
Export Share	0.416***	0.701***	0.286***	0.428***	0.418***	0.709***	0.410***	0.689***
	(0.068)	(0.116)	(0.091)	(0.160)	(0.069)	(0.118)	(0.070)	(0.120)
Revenue Change 19-20	-0.043	-0.193	0.494*	0.761*	-0.042	-0.193	-0.048	-0.133
	(0.206)	(0.330)	(0.286)	(0.462)	(0.207)	(0.331)	(0.216)	(0.342)
ROA 19	-0.001	-0.003	-0.008***	-0.015**	-0.001	-0.003	-0.001	-0.003
	(0.001)	(0.002)	(0.003)	(0.006)	(0.001)	(0.002)	(0.001)	(0.002)
Value Added per Employee 19	0.123	0.028	2.927**	5.063**	0.122	0.026	0.116	0.015
	(0.124)	(0.045)	(1.375)	(2.529)	(0.124)	(0.044)	(0.119)	(0.038)
Industry x Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.114	0.097	0.153	0.135	0.112	0.095	0.113	0.099
R^2 Adj.	0.075	0.057	0.125	0.106	0.073	0.056	0.073	0.058
N Firms	1,618	1,618	718	718	1,618	1,618	1,536	1,536

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 a 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 definition in Section 6). For details on the construction of *Precautionary Labor* see Section 4.3. Control variables are as of 2019. Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.4: Summary Statistics of 10 Largest Occupations

	2019				2018				Voc Share	Shortage
	Mean	p50	p90	N	Mean	p50	p90	N		
Occupations in machine-building and -operating, Specialist	9.93	6.01	24.57	1571	10.09	6.03	25.06	1551	87.26	1
Occupations in business organisation and strategy, Specialist	7.05	4.37	15.62	1940	7.15	4.36	15.46	1916	71.30	0
Occupations in warehousing and logistics, Unskilled or semi-skilled	6.59	2.99	17.53	1479	6.77	3.12	17.95	1476	64.63	0
Occupations in chemistry, Specialist	10.59	2.88	37.43	546	10.59	3.09	35.98	543	84.87	0
Occupations in metalworking, Specialist	7.53	3.20	21.99	800	7.81	3.38	22.75	787	89.43	1
Office clerks and secretaries, Specialist	4.43	2.12	10.23	1898	4.63	2.22	10.55	1897	76.47	0
Occupations in purchasing and sales, Complex specialist	4.56	2.49	10.64	1817	4.64	2.56	10.53	1798	67.05	0
Occupations (techn) in production planning and scheduling, Complex specialist	3.04	2.32	6.31	1610	3.08	2.33	6.45	1592	69.40	0
Occupations in warehousing and logistics, Specialist	4.23	2.47	9.16	1610	4.28	2.44	8.84	1602	79.11	0
Occupations in technical research and development, Highly complex	3.22	1.47	7.29	1138	3.30	1.42	7.55	1114	12.57	1

Notes: The table shows summary statistics of the firm-level shares of the 10 largest occupations in the sample (as of 2019). All numbers are in percent. The last two columns show occupation-level information on the aggregate share with vocational training or whether it is a shortage occupation.

Table D.5: Summary Statistics for Firms with Above/Below Median FSHC

(a) Vocational Training-Based

	Below Median Voc Training-Based					Above Median Voc Training-Based					Diff means
	Mean	p10	p50	p90	N	Mean	p10	p50	p90	N	p-value
Core Financial Information (2019)											
Assets (mil EUR)	211.23	12.98	47.67	309.62	1155	168.86	15.57	43.90	225.75	1155	0.47
Revenue (mil EUR)	203.01	20.88	73.17	361.00	1155	172.22	25.72	73.06	291.98	1155	0.24
Employees	381.59	42.00	194.00	705.00	1155	419.68	70.00	255.00	747.00	1155	0.34
Leverage (pp)	61.52	24.87	61.44	92.86	1155	57.14	21.96	57.42	90.11	1155	0.00
Cash/Assets (pp)	11.44	0.03	5.28	31.47	1155	8.03	0.02	3.33	22.57	1155	0.00
ROA (pp)	8.11	-4.21	6.64	23.33	1155	6.90	-4.42	5.59	20.03	1155	0.03
Value Added per Employee (mil EUR)	0.17	0.06	0.11	0.24	824	0.10	0.05	0.08	0.15	820	0.00
Firm-Level Employment Characteristics (2019)											
Avrg Age (years)	42.55	37.31	42.82	47.39	1155	42.98	39.13	43.12	46.85	1155	0.00
Avrg Wage (EUR, daily, FT)	143.21	103.96	142.70	181.87	1155	121.18	88.67	120.55	153.70	1155	0.00
Avrg Tenure (years)	9.23	4.37	8.88	14.33	1155	11.78	6.47	11.38	17.66	1155	0.00
Information on Exports and FX Volatility											
Export Share (2019)	0.44	0.05	0.45	0.84	1155	0.45	0.07	0.47	0.80	1155	0.45
1(Exports to Outside Europe)	0.84	0.00	1.00	1.00	559	0.81	0.00	1.00	1.00	633	0.26
1(Financial Hedging 2019)	0.27	0.00	0.00	1.00	1155	0.26	0.00	0.00	1.00	1155	0.42
Number of Banks	2.42	1.00	2.00	4.00	1094	2.80	1.00	3.00	5.00	1086	0.00
1(Relationship Bank: Local)	0.46	0.00	0.00	1.00	1094	0.58	0.00	1.00	1.00	1086	0.00
1(Relationship Bank: Grossbank)	0.84	0.00	1.00	1.00	1094	0.86	0.00	1.00	1.00	1086	0.12

(b) Shortage Occupation-Based

	Below Median Short Occup-Based					Above Median Short Occup-Based					Diff means
	Mean	p10	p50	p90	N	Mean	p10	p50	p90	N	p-value
Core Financial Information (2019)											
Assets (mil EUR)	178.44	13.10	43.83	240.02	1155	201.65	14.73	47.88	277.65	1155	0.69
Revenue (mil EUR)	185.38	23.92	76.69	333.57	1155	189.86	21.44	70.71	325.10	1155	0.87
Employees	301.37	37.00	172.00	581.00	1155	499.90	92.00	283.00	906.00	1155	0.00
Leverage (pp)	60.54	23.38	60.19	93.99	1155	58.11	23.74	58.08	89.66	1155	0.07
Cash/Assets (pp)	9.73	0.03	4.17	27.50	1155	9.74	0.03	4.41	27.61	1155	0.97
ROA (pp)	7.84	-3.99	6.34	22.41	1155	7.18	-5.16	5.94	20.92	1155	0.24
Value Added per Employee (mil EUR)	0.17	0.05	0.10	0.25	816	0.09	0.05	0.09	0.15	828	0.00
Firm-Level Employment Characteristics (2019)											
Avrg Age (years)	42.82	37.90	43.00	47.60	1155	42.70	38.55	42.96	46.62	1155	0.43
Avrg Wage (EUR, daily, FT)	132.66	91.58	130.61	176.71	1155	131.74	96.98	131.15	166.21	1155	0.46
Avrg Tenure (years)	9.85	4.56	9.50	15.01	1155	11.16	5.64	10.83	16.90	1155	0.00
Information on Exports and FX Volatility											
Export Share (2019)	0.41	0.04	0.40	0.80	1155	0.47	0.07	0.50	0.83	1155	0.00
1(Exports to Outside Europe)	0.78	0.00	1.00	1.00	549	0.86	0.00	1.00	1.00	643	0.00
1(Financial Hedging 2019)	0.27	0.00	0.00	1.00	1155	0.25	0.00	0.00	1.00	1155	0.28
Number of Banks	2.51	1.00	2.00	4.00	1088	2.71	1.00	3.00	4.00	1092	0.00
1(Relationship Bank: Local)	0.47	0.00	0.00	1.00	1088	0.57	0.00	1.00	1.00	1092	0.00
1(Relationship Bank: Grossbank)	0.84	0.00	1.00	1.00	1088	0.86	0.00	1.00	1.00	1092	0.12

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

Table D.6: Occupational Composition Across Time

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

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

Table D.7: Heterogeneity by Cash and Leverage

	Dep. Variable: FX-Induced CF Volatility			
Split:	High Cash		Low Leverage	
	sd	max	sd	max
Precautionary Labor	-7.070**	-14.120***	-8.850***	-17.796***
	(2.748)	(5.235)	(3.055)	(5.729)
Split × Precautionary Labor	-3.693	-5.071	1.255	4.680
	(3.003)	(5.475)	(2.992)	(5.424)
Split	0.174*	0.199	-0.019	-0.132
	(0.098)	(0.174)	(0.099)	(0.174)
Log Assets 19	0.008	0.001	0.007	0.003
	(0.020)	(0.034)	(0.019)	(0.033)
Export Share	0.526***	0.882***	0.525***	0.876***
	(0.068)	(0.124)	(0.066)	(0.120)
Revenue Change 19-20	-1.658***	-3.059***	-1.490***	-2.748***
	(0.561)	(1.024)	(0.519)	(0.952)
ROA 19	-0.006***	-0.011***	-0.005***	-0.011***
	(0.002)	(0.003)	(0.002)	(0.003)
Industry x Region FEs	Yes	Yes	Yes	Yes
F main effect (SW)	9.73	9.73	9.29	9.29
F interaction (SW)	28.46	28.46	25.58	25.58
Overid. (Hansen J) p-value	0.378	0.205	0.315	0.174
N Firms	2,274	2,274	2,274	2,274

Notes: The table reports the estimated coefficients from specification (R3) instrumenting *Precautionary Labor* with both instruments and allowing for heterogeneity in cash and leverage. *High Cash* means an above-median cash-to-asset ratio in 2019. *Low Leverage* means an above-median equity-to-asset ratio in 2019. The F-statistics provided are Sanderson-Windmeijer per-regressor first-stage F-statistics. 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 definition in Section 6). Robust standard errors are reported in parentheses. Stars denote statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.