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# LEARNING TO FORECAST THE HARD WAY—EVIDENCE FROM GERMAN REUNIFICATION

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**ABSTRACT**

Do firms learn to forecast future business conditions after structural changes to the economy? How long does it take? We exploit German Reunification as a natural experiment, where Eastern are treated with ignorance about the distribution of market states, to test Bayesian learning. As predicted, Eastern firms initially forecast future business conditions worse than Western ones, but this gap gradually closes over a decade following Reunification. The slow convergence stems from differences in forward expectations rather than realized market conditions. These results warn of costly and drawn out adjustments to regime changes, as the trade wars, COVID19 and Brexit.

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# 1. Introduction

Virtually all firm decisions, either implicitly or explicitly, depend on forecasts of the future. Future business conditions are always uncertain and often cyclical, but occasionally the economy changes so severely that firms must learn the market anew. Recently, it seems, 'occasionally' has become 'often:' 2018 brought the US-China Trade War, 2020 the COVID19 pandemic, and 2021 Brexit. These events are unlikely to be one-off shocks but are expected to permanently change international economic relations or even consumer and firm behavior. With these upheavals to supply, demand and trade conditions as a backdrop, this paper asks, "How do firms learn to forecast again after a structural change to the economy? How long does it take?"

At first blush, measuring the rate at which young firms' forecasts improve over time seems simple, but since firm age correlates with unobserved firm and market attributes affecting forecast quality, any such estimate of the learning rate would be biased. For example, in addition to new firms being smaller (for which we can control), their employees also tend to be younger and have different human capital, and their markets tend to be newer and utilize different technologies. Thus, another approach is required.

The ideal experiment would exogenously place a cross-section of naive firms into a new market environment alongside very experienced but otherwise similar counterparts and compare their forecasts of subsequently shared market conditions over time. German Reunification was just such an event.[1,2] The unique microdata from a German firm survey, the Ifo Business Climate Survey (*Geschäftsklimaindex*), allows us to quantify how fast East German firms learn to forecast business conditions under the quasi-experiment of German Reunification. The widely cited survey, established in 1949, has collected the near term expectations and assessment of current business conditions from a large cross section of German manufacturing establishments. Reported firm expectations and realizations allow us to calculate monthly, firm-level forecast errors.

Figure 1 provides descriptive evidence for the impact of Reunification on Eastern firms forecast errors. It plots forecast error magnitudes by Western firms since 1980 and Eastern

[1] Germany reunited on October 3rd 1990. By July 1st of that year, an economic and monetary union had already been established.

[2] Level productivity differences between firms, whether on the other side of the Iron Curtain or town, should not influence forecast quality, since firms know these idiosyncratic factors.

ones after Reunification. Initially, Eastern firms made much larger forecast errors than

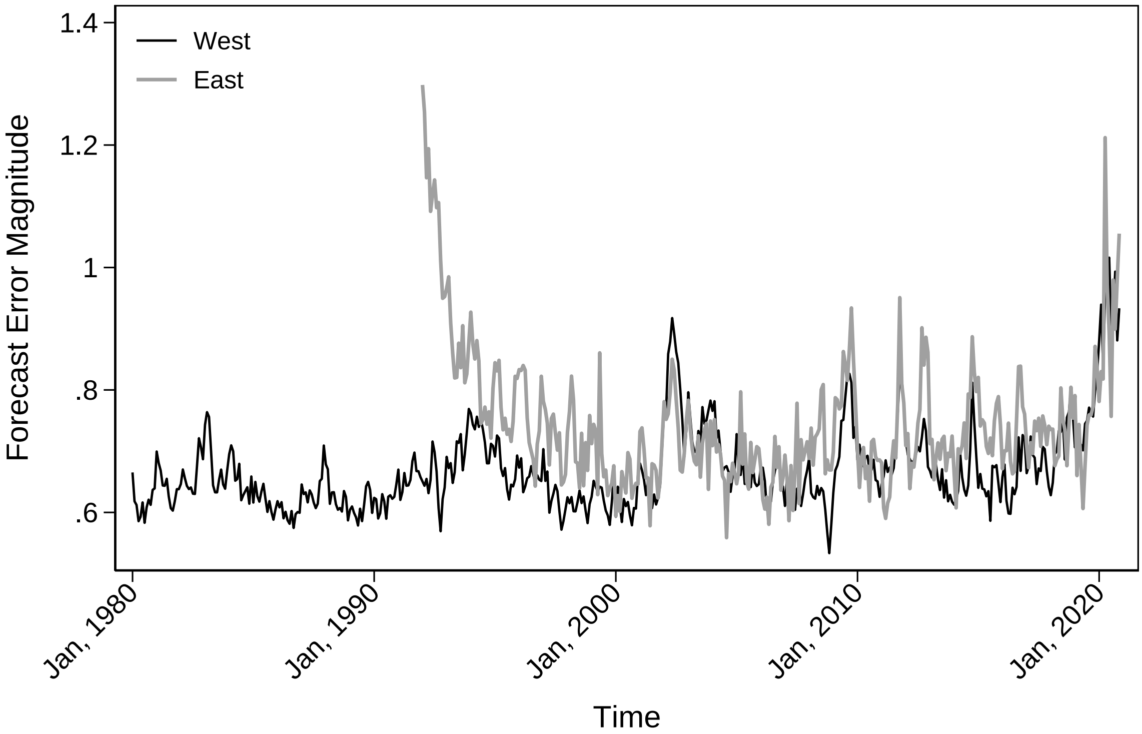



**Figure 1:** Forecast Errors in East and West Germany

*Notes*: This graph plots the monthly average of the squared forecast errors for East (from 1992) and West Germany. Forecast errors are constructed from qualitative survey questions on business condition (*Geschäftslage*) expectations and realizations.

Western ones. There is no indication that Western firms had similar forecasting difficulties immediately after Reunification; they did not have to learn a new market. Over time, forecast errors in the East decreased and converged to Western levels. Note that over the 40 years we observe, only the Covid19 shock in early 2020 caused forecast error magnitudes comparable to those of Eastern firms after Reunification.

We argue this convergence in forecast errors depicted in Figure 1 is driven by Eastern firms learning the new market process after the shock of Reunification. Or equivalently, Eastern firms' idiosyncratic uncertainty over market understanding dwindles. First, our empirical results do not refute the predictions of Bayesian firm learning. Second, our empirical model controls for alternative explanations like convergence in underlying market states, changes in Eastern consumer behavior, changes in firm idiosyncratic circumstances, or new Western owners learning the Eastern market. Controlling for firm unobserved heterogeneity shows that convergence is not purely due to survival of the best forecasters either. Finally, our explanation for forecast error reduction in the East aligns with several pieces of circumstantial evidence, including Eastern managers' recognition of a deficiency in their understanding of market economies. In 1991 West German firms hosted East German managers as interns. About 70 percent of these interns self-reported having a poor knowledge of market economics; more than 85 percent of their Western hosts shared that assessment (Icks, 1992).

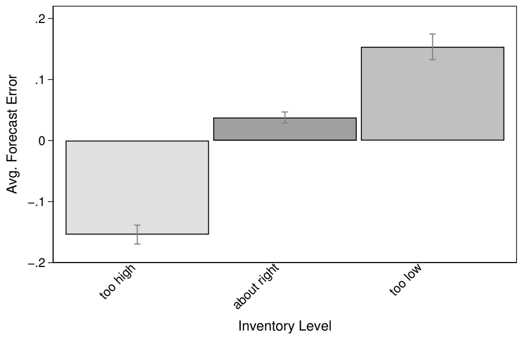
Using the coefficient estimates for our empirical model of convergence, we find that Eastern forecast errors converge to Western levels roughly nine years after the beginning of our Eastern sample in 1992, at a rate of about five percent per annum. Arguably, learning is slow given that formal institutions converged immediately and business conditions very quickly—indeed subjective *realized* business conditions (ignoring level differences) converged just a year after the beginning of our Eastern sample.[3]

Given that firms' predictions and realizations of business conditions are subjective and qualitative, one might ask whether predictions are consistent with firm decisions and whether forecast errors are consistent with performance outcomes. Figure 2 depicts the relationship between firms' directional forecast errors and their assessment for inventory, profitability and capacity utilization over the period that they previously forecasted. Overly-optimistic firms (indicated by negative forecast errors) report too high inventories, bad profitability, and low capacity utilization —exactly as one would expect from economically meaningful firm-level forecast data.[4] Moreover, consistent with the results of Tanaka et al. (2020) we show in Table B.6 in Appendix B that forecast errors also negatively correlate with accounting profitability. Forecast errors matter for firm performance. They are costly in terms of capacity utilization, inventory, and therefore profitability. Appendix B provides additional evidence that our survey data is informative.

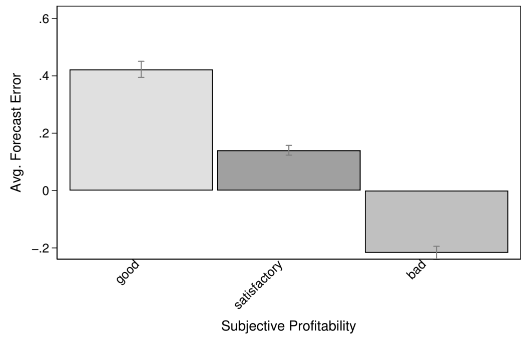
We contribute to a growing empirical literature testing imperfect information's impact on firms' expectation formation (Coibion and Gorodnichenko, 2012, 2015; Coibion et al.,

[3]Famously, Dahrendorf (1990) suggests that legal, economic, and cultural transitions take, six month, six years, and six decades, respectively. Our results are broadly in line with that intuition.

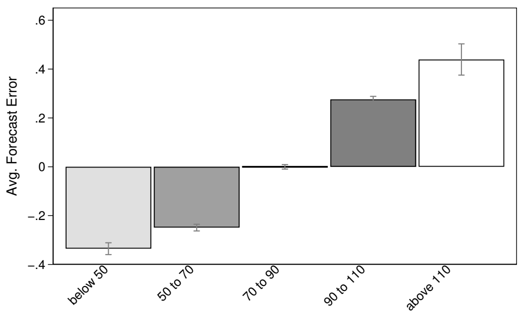
[4]The ifo's Business Climate Survey is widely used in the economics literature (Nerlove, 1983; Bachmann et al., 2013; Bachmann and Elstner, 2015; Massenot and Pettinicchi, 2018; Enders et al., 2019b).




**(a)** Inventory Level




**(b)** Subjective Profitability




**(c)** Capacity Utilization

**Figure 2:** Forecast Errors and firm performance

*Notes*: This graph plots average forecast errors over self-reported inventory levels (top left), profitability (top right), and capacity utilization (bottom) including 95% confidence intervals. The confidence intervals take into account clustering at the firm level. The survey question for capacity utilization allows for the following answers: 30, 40, 50, 60, 70, 75, 80, 85, 90, 95, 100, >100. The capacity question explicitly defines “usual” full capacity as 100 per cent. The questions are asked quarterly. We assume they are constant within quarters and take the six month ahead average. Responses are measured as ordered categories. Forecast errors are for a qualitative survey question on business condition (*Geschäftslage*).

2018, 2020).[5,6] It concludes that inattention (Sims, 2003; Coibion et al., 2020) and information rigidities, in particular noisy signals (Coibion and Gorodnichenko, 2012), drive firms' backcast/forecast errors. Coibion et al. (2018) collected firms' assessments and expectations of macroeconomic conditions in New Zealand. They find that firms update their estimates in a Bayesian fashion after receiving an informative signal about the true state of the macro-economy. In these studies firms understand the data generating process (DGP) but volatility in the realizations leave estimates uncertain. Adding new information in the form of a signal allows firms to refine their estimates in that period (only). Our model adds another source of uncertainty, one that is firm specific and continuously decreases for each firm over time—misunderstanding of the DGP. In our model firms do not know the DGP, but gradually learn it, while, like in the extant literature, incorporating signals along the way to improve their immediate forecasts.

Here we investigate the resolution of the ignorance shock firms receive to their understanding of the DGP after a real-world structural change to the market process. A similar type of learning occurs when firms are young (Massenot and Pettinicchi, 2018). In a recent working paper, Chen et al. (2018) show that firms learn to forecast own sales with experience in new markets. But age and market entry are not random and/or correlate with other unobservables like industry maturity or staff experience. To the best of our knowledge, ours is the first natural experiment based test of how firms *learn* to forecast the future over time.

Here we do not relate learning to firm performance, decisions, or welfare.[7] However, we showed above that forecast errors correlate with various measures of the former. Also, there is clear prior evidence that all three are affected by expectations and forecast errors (Coibion et al., 2018; Massenot and Pettinicchi, 2018; Enders et al., 2019a; Coibion et al., 2020; Tanaka et al., 2020). Tanaka et al. (2020), in particular, shows that not only

[5]See these papers for references to work that analyzes the theoretical implications of expectations formation with imperfect information.

[6]From a purely statistical perspective expectation formation is inconsistent with the full information, rational expectations hypothesis. Nerlove (1983) empirically tests the expectations formation process using Ifo's Business Climate data for the period 1977/78 (an earlier subset of our data) and comparable French data. He finds that a simple error-correction model, though "devoid of economic content" explains observed expectations "surprisingly well" (p. 1267). Massenot and Pettinicchi (2018) use the Ifo data to confirm that firms forecast using extrapolation. Pesaran and Weale (2006) review the literature testing rational expectations with qualitative survey data.

[7]Our estimated learning rate might be used to calibrate general equilibrium models.

do firms' input and investment decisions depend on forecasts but so do profitability and productivity. Given this evidence, our results suggest that time required to learn the market economy additionally slowed productivity convergence between East and West after Reunification. Our findings also provide a firm-level mechanism (from better understanding to lower forecast errors to higher productivity) for the prior finding that aggregate uncertainty negatively affects aggregate output (Bachmann et al., 2013; Bloom, 2014).

Our results stress that firms need time to learn to operate in new settings, which is relevant for policy making that relies on managing expectations.[8] Policy makers do not only have to overcome inattention they also need to wait until firms understand. The lessons of this switch to capitalism, though more drastic than most changes to business environments, may help set realistic expectations for how quickly firms adjust to other sweeping market changes like the global pandemic, new trade rules, or redrawn political boundaries. New formal institutions might be built quickly, but firms need longer to learn how to operate in the new regime. Learning, even when rational, slows down the response to market or policy changes.

## 2. Theoretical Framework

A stylized model of Bayesian firm-learning articulates a mechanism that we can test empirically with our particular data. We require a model to interpret firms' responses to the survey questions, because these do not directly ask about the theoretical objects of interest but rather about aggregates or functions of them. Surveyed firms report correlated but different realized business conditions (literally *Geschäftslage*) in each period and different forecasts of their future changes. We posit that this pattern arises because what firms report as business conditions is a mixture of idiosyncratic firm-level conditions and shared market conditions. For simplicity, we assume that firms know the DGP behind the idiosyncratic firm portion, but they must learn (the parameters of) the DGP behind the market portion. We aim to analyze this previously empirically unstudied source of uncertainty—firms' understanding of the market-–distinct from previously examined (and occasionally muddled together) sources of uncertainty, like market volatility and signal

[8]Expectation management is important in monetary (e.g. Wiederholt, 2015) and fiscal policy but also, as the example of Brexit shows, in trade policy.

noise. Although the Bayesian learning and signal processing components we combine are standard, and even though our model's theoretical insights are well-known, laying it out formally clarifies the mapping from our data, to the underlying theoretical objects and our hypotheses.

Formally, suppose at the beginning of period $t$, nature draws two hidden independent states relevant for firm $i$'s change in business conditions: $X_{it}$ is an idiosyncratic firm state distributed according to a firm specific distribution $F_i$, known to the firm, with mean $\mu_{Xi}$ and variance $\sigma^2_{Xi}$, and $Y_t$ is a market state common to all firms distributed according to $G\left[Y_t;\mathbf{z}\right]$ with vector of parameters $\mathbf{z}$, mean $\mu_Y\left[\mathbf{z}\right]$ and variance $\sigma^2_Y[\mathbf{z}]$, where $X_{it}$ and $Y_t$ are independent. For simplicity, we assume firm level business conditions are the sum of these variables: $S_{it}{=}X_{it}{+}Y_t$.

The information available at the beginning of period $t$ includes all previous state realizations $\Omega_{it} = X_{it-1}, \ldots, X_{i1}, Y_{t-1}, \ldots, Y_1$ and a firm specific signal of the current market state $\hat{Y}_{it} = Y_t + \varepsilon_{it}$, where $\varepsilon_{it}$ is firm specific white noise. The signal of market state $\hat{Y}_{it}$ is the private information firm $i$ gets from the media or other sources about the state of the market in the next period. Thus, $X_{it}|\hat{Y}_{it}, \Omega_{it} = X_{it}$ and $Y_t|\hat{Y}_{it}, \Omega_{it}$ remain independent.

Firms do not know $\mathbf{z}$; they must learn it. Firm $i$ holds beliefs $\hat{\mathbf{z}}_{it}$ in the form of a distribution over the possible values of $\mathbf{z}$ in time $t$. These beliefs are Bayesian updated with all information in $\Omega_{it}$ at the end of each period $t$. These beliefs converge as $t \rightarrow \infty$ to a distribution with all mass on $\mathbf{z}$. Throughout, we refer to firm $i$'s distributed beliefs about the unknown parameter vector $\mathbf{z}$ as its (distribution of) *understanding.*

The firm makes a prediction about its state of business equal to the sum of conditional forecasts about its idiosyncratic and market states:

$$\hat{S}_{it} = E[X_{it} + Y_t|\hat{Y}_{it}, \Omega_{it}] = \mu_{Xi} + E[Y_t|\hat{Y}_{it}, \Omega_{it}]$$

At the end of period $t$ the realized state variables are revealed, and a directional forecast error $S_{it} - \hat{S}_{it}$ is computed. A positive value indicates that the firm was pessimistic—it predicted a worse change in business state than actually occurred. A negative value indicates that the firm was optimistic—it predicted a better change in the state of business than actually occurred. We are interested in the expected magnitude of this error or so-called mean squared error (MSE):

$$
\begin{aligned}
MSE_{it} &= E[(S_{it} - \hat{S}_{it})^2 | \hat{Y}_{it}, \Omega_{it}] \\
&= E[((X_{it} + Y_t) - E[X_{it} + Y_t | \hat{Y}_{it}, \Omega_{it}])^2] \\
&= \sigma_{Xi}^2 + Var[Y_t | \hat{Y}_{it}, \Omega_{it}]
\end{aligned} \tag{1}
$$

where the last equality follows from the independence of $X_{it}$ and $Y_t$ (so that $Cov[X_{it}, Y_t|\hat{Y}_{it}, \Omega_{it}] = 0$). Since the firm knows $\sigma_{Xi}^2$, and it does not vary with factors beyond the firm or time, changes in the $MSE_{it}$ with respect to market factors or time are equivalent to changes in $Var[Y_t|\hat{Y}_{it}, \Omega_{it}]$.

In our empirical setting, we treat Western firms as if their beliefs about the parameters of the market state DGP have already converged to their true values, but Reunification treats Eastern firms with 'ignorance.' Immediately following Reunification Eastern firms' distributions of beliefs about the parameters of the market state DGP have very high variance, and in general, have the wrong mean. With experience their belief distributions converge around the true values through a standard Bayesian updating process. Our empirical analysis will confirm the telltale signs of this learning process:

**Hypotheses:**

(i) Assuming the average variance in idiosyncratic firm states is at least as high in the East as in the West (*i.e.* $E_i[{\sigma_{Xi}}^2] \geq E_j[{\sigma_{Xj}}^2], i \in East, j \in West$), then immediately following Reunification, average forecast error magnitude in the East exceeds the average forecast error magnitude in the West ($E_i\left[MSE_{i0}\right] > E_j\left[MSE_{j\infty}\right] > 0, i \in East, j \in West$),

(ii) Average forecast error magnitude in the East declines with experience ($E_i\left[\frac{d}{dt}MSE_{it}\right] < 0, i \in East$),

(iii) The average rate of forecast error reduction slows with experience ($E_i\left[\frac{d^2}{dt^2}MSE_{it}\right] > 0, i \in East$), and

(iv) Assuming the average variance in idiosyncratic firm states in the East equals those in the West (*i.e.* $E_i[{\sigma_{Xi}}^2] = E_j[{\sigma_{Xj}}^2], i \in East, j \in West$), then average forecast error magnitude in the East converges to the average forecast error magnitude in the West ($lim_{t\to\infty}E_i\left[MSE_{it}\right] = E_j\left[MSE_{j\infty}\right], i \in East, j \in West$).

Formally proving these intuitive results requires slightly more structure. For an instantiation of the above model and proof of the hypotheses under the assumption that the market state, prior beliefs about the market state distribution's parameters, and signal noise are all normally distributed can be found in Appendix A.

Note that while the conditions about the relative variances of Eastern versus Western idiosyncratic firm states in hypotheses (i) and (iv) are theoretically restrictive, these conditions can be empirically controlled for. In particular, our regressions control for the variance in idiosyncratic firm states. Hence, from an empirical perspective, hypothesis (i) reduces to "Immediately following Reunification, average forecast error magnitude in the East exceeds the average forecast error magnitude in the West," and hypothesis (iv) to "Average forecast error magnitude in the East converges to the average forecast error magnitude in the West," without restrictions on the distribution of idiosyncratic firm states.

# 3. Data and Forecast Error Measurement

We test our predictions using data from the Ifo Institute's Business Climate Survey, one of the oldest surveys of firm-level, business condition expectations and realizations in existence.[9] Ifo began surveying firms in the Federal Republic of Germany in November 1949; firms from former East Germany were added beginning in 1991. As one might expect of such a critical management function as forecasting market conditions, according to Ifo's own meta-analysis, the survey respondents are predominantly from management (65%) followed by finance (23%) and marketing (8%) (Sauer and Wohlrabe, 2019). Our sample has monthly observations for the years 1980 to 2020 for West Germany and for 1992 to 2020 for former East Germany. We drop Eastern observations for 1991, because administrative difficulties render these earliest Eastern observations unreliable, and it gives Eastern firms a few months to learn the survey's mechanics. Virtually, all Eastern firms are the result of a privatization process right after Reunification. Many privatized units were bought by Western or international firms but we do not observe ownership.

[9]For a review of the most popular surveys on expectations across countries and economic actors (households, firms, professional forecasters) see Pesaran and Weale (2006). Recently, there have been efforts to gather more large-scale quantitative survey data on firm expectations including subjective probability distributions of future events. Examples are the Management and Organizational Practices Survey (MOPS) in the U.S. and the Management and Expectations Survey run by the Office of National Statistics in the UK.

The data only allows us to observe whether a survey was mailed to one of the Eastern states.

The data is collected at the product level, and we include manufacturing firms only. In 1980 we have more than 4000 products in the cross-section. By the end of our sample, attrition reduces the cross-section to about 2500 products. Following Nerlove (1983, footnote 15), we treat product-level observations as independent. The panel is unbalanced and has gaps, but we do not observe firms' entry to or exit from the market.

We construct our forecast error measure from two survey questions about the state of business (*Geschäftslage*). The survey question regarding the realization of the current state of business reads:

> *(i) Current situation: We assess our state of business for product X to be (a) good, (b) satisfactory, or (c) bad.*

The question about the expectation reads:

> *(ii) Expectations for the next six months: Our state of business for product X will be (a) better, (b) about the same, or (c) worse.*

That the responses are qualitative and trichotomous, and that the current month's situation is specified in levels, while expectations are in changes over six months requires some manipulation of the raw data. Our approach is to aggregate responses under (i) to six month averages and to translate levels into changes given assumptions about latent thresholds on levels that cause firms to change their answer to (ii). The details of this approach are in the next subsection, which the casual reader can safely skip.

The Ifo Business Climate Survey not only asks firms about their state of business (*Geschäftslage*), but also demand (*Nachfragesituation*), and own domestic production (*inländische Produktionstätigkeit*). Previous papers have calculated forecast errors from different survey questions but state of business best captures market-level business conditions. First, the survey only solicits both expectation and realization for state of business and domestic production. Massenot and Pettinicchi (2018)'s qualitative forecast errors apparently compare state of business expectations to demand realizations. Nerlove (1983, p. 1258) also treats the state of business as a proxy for demand; however, since the survey explicitly includes a separate question on demand, we assume that state of business, as discussed in Section 2, encompasses more. In any case, we show that our empirical results are robust to defining forecast errors over own domestic production.

### 3.1. Forecast error calculation

To make the forecast horizon of survey question (i) above consistent with that of (ii) we code (i), the current business state assessment by firm $i$ in month $t$, as $S_{it} \in \{bad = -1, satisfactory = 0, good = +1\}$, so that we may compute the average state of business over the next six months as the realization $\overline{S}_{it} = \frac{1}{6}\sum_{k=t+1}^{t+6} S_{ik} \in [-1, 1]$. From here, we suppress index $i$ to ease readability. If firms reported the expected (average) state $\hat{S}_t$ we could calculate forecast errors straight away.

But the forecaster reports, in question (ii), the expected *change* $\hat{\Delta}_t \in \{worse = -1, same = 0, better = +1\}$ relative to the current state. We suppose that the forecaster computes these expected changes as a function of the current state $S_t$, the expected future state $\hat{S}_t$, and some unobserved thresholds, $L[S_t]$ and $H[S_t]$. The thresholds are functions of the current state, such that $-1 \leq L[S_t] \leq H[S_t] \leq +1$, for all $S_t$ and denote levels at which the future state transitions from one category to the next. The right side of (2) gives the formula that we assume the forecaster uses to compute $\hat{\Delta}_t$; however, from our perspective as the empiricist, $\hat{\Delta}_t$ is reported data.

On the other hand, to obtain a forecast error we must calculate a corresponding *realized change* in the state of business $\Delta_t \in \{worse = -1, same = 0, better = +1\}$. The realized change is a function of the current state $S_t$, the realized future state $\overline{S}_t$, and the same unobserved thresholds, $L[S_t]$ and $H[S_t]$. The formula is on the left:

$$\Delta_t \equiv \begin{cases} worse = -1 & -1 \leq \overline{S}_t < L[S_t] \\ same = 0 & L[S_t] \leq \overline{S}_t \leq H[S_t] \\ better = +1 & H[S_t] < \overline{S}_t \leq +1 \end{cases}; \quad \hat{\Delta}_t \equiv \begin{cases} worse = -1 & -1 \leq \hat{S}_t < L[S_t] \\ same = 0 & L[S_t] \leq \hat{S}_t \leq H[S_t] \\ better = +1 & H[S_t] < \hat{S}_t \leq +1 \end{cases} \tag{2}$$

Having translated (i) and (ii) into realized and expected changes over a six month horizon, we can define the directional forecast error as the realized change minus expected change: $\Delta_t - \hat{\Delta}_t$.

The above abstraction of the forecaster contains six different thresholds (*i.e.* $L[S]$ and

$H[S]$ for $S \in \{bad, satisfactory, good\}$ ), which determine what future state realizations are considered *better*, the *same*, and *worse* than the current state. We cannot know precisely where the forecaster sets these, but we show that our empirical results are robust to variation of $L[S]$ and $H[S]$ within reasonable constraints. First, these thresholds must weakly increase in the current state, i.e. $L'[S] \geq 0$ and $H'[S] \geq 0$. For example, if the current state is *good* then reaching a *better* state requires surpassing a higher threshold than if the current state is *bad*, and likewise if the current situation is *bad,* then reaching a *worse* state requires falling below a lower threshold than if the current state is *good.*

At the extremes of the state space (*i.e.* *bad* and *good*), forecasts of even more extreme states (*i.e.* *worse* and *better*, respectively) create an internal inconsistency. Our abstraction offers a resolution. Consider a firm in a *good* state, predicting the *same* future state. It will make a +1 error if average future realizations fall in the interval $[H[good], +1]$, say if all future realizations were *good* and $H[good]$ is set strictly less than +1. One could argue that this should not be an error since we do not really know if observing the next six future states in a row as *good* really means that the firm's state of business improved—it was, after all, *good* to begin with. To rule this out as an error one would set $H[good] = +1$. On the other hand, because forecasters seem to calibrate notions of *good*, *satisfactory*, and *bad* on recent experience, reporting the next six states of business as *good* is unusual even for a firm currently reporting a *good* state of business and could reasonably be interpreted as an improvement in business state. Setting $H[good]$ below +1 captures some of this information. In general, increasing $H[\bullet]$, and decreasing $L[\bullet]$ makes it harder to record a (large) error.

Imposing symmetry halves the number of free thresholds from six to three: for all $S$, $H[good] = -L[bad]$., $H[satisfactory] = -L[satisfactory]$ and $H[bad] = -L[good]$. This is both intuitive and simplifies robustness checking. In our main specifications we use the following parameterization: $H[good] = \frac{2}{3}$, $H[satisfactory] = \frac{1}{3}$ and $H[bad] = 0$. However, Appendix C shows that both more and less conservative parameter choices produce similar results. Finally, we measure the forecast error magnitude as the square of the directional forecast error (*i.e.* $MSE_{it}$), but we demonstrate that our results are robust to using the absolute value.

# 4. Empirical Specification and Identification

Relatively homogeneous Germany was abruptly divided in 1949 and, for four decades, firms in East Germany operated under a master-planned, communist economy. For these firms of all sizes, maturities, and across the spectrum of industries, market states were dictated, not predicted. Then suddenly, and quite unexpectedly, with German Reunification in 1990, these firms were thrust into the free market economy of the West. We identify our theoretical predictions using forecast error differences between East and West after Reunification. Obviously, we do not observe survey responses for Eastern firms before Reunification and assume that the ex-ante difference in forecast errors was zero.

We estimate the following reduced form empirical model:

$$\text{FE}_{ijm} = \beta\text{East}_i + \sum_{n=1}^{4} \phi_n \text{Trend}_m^n \times \text{East}_i + \gamma\text{Imp}_{im} + \delta_{mj} + \theta_i + \epsilon_{ijm} \tag{3}$$

where $i$ indexes firms, $j$ industries, and $m$ month-years. The dependent variable is the squared firm level forecast error magnitude (FE), a categorical variable taking values 0,1, or 4. It is the empirical proxy for $MSE$ in the theory above. We test robustness to using the absolute forecast error instead.

For the Eastern firm indicator ($\text{East}_i$), our framework predicts that the average firm in the East makes larger forecast errors than in the West ($\beta > 0$). Note, that due to the inclusion of the trend interaction $\beta$ gives the initial Eastern forecast error. Theoretically, firms' beliefs about the DGP's parameters converge to the true ones at an ever slowing rate into the infinite future. This can be modeled as an infinite polynomial in which the coefficients of each term diminish in size and alternate in sign (where the first is negative). Empirically, a fourth order polynomial suffices for our data. Given higher forecast errors in the East initially, convergence implies $\phi_1 < 0$, $\phi_2 > 0$, $\phi_3 < 0$, and $\phi_4 > 0$, where $|\phi_1| > |\phi_2| > |\phi_3| > |\phi_4|$. The monthly trend variable (Trend) is divided by 12 and normalized to $1992 = 0$ to facilitate the interpretation of the estimated coefficients below. We do not include a time trend for the West as our framework predicts no significant change in Western errors over time (our empirical counterfactual).

To identify convergence correctly and to rule out mechanisms other than firm-learning, we add a number of controls. Note that we do not need to control for any institutional differences as, uniquely among transition countries, East Germany immediately received developed Western institutions (*e.g.* legal system, property rights, social welfare) as well as full global market access (Dornbusch et al., 1992).

Empirically, convergence might capture not just learning of the market by Eastern firms but stabilization of firm-level factors, like labor supply or equipment reliability in those same firms. We control for these firm-level idiosyncrasies in two ways. First, we include a time varying indicator, Imp, that takes the value one if the firm reports any impairment to production.[10]

Second, in one specification we also include firm fixed effects ($\theta_i$). These absorb time-invariant firm heterogeneity, especially variance in idiosyncratic firm states (i.e. $\sigma^2_{Xi}$ in the theoretical framework of Section 2). Including these fixed effects, empirically controls for $E\left[\sigma^2_{Xi}\right]$ for all firms $i$ such that the conditions on Hypotheses (i) and (iv) are satisfied, allowing us to unambiguously sign their predictions: (i) Eastern firms will initially make larger errors than Western ones, and (iv) these will converge to the same level over time. These firm fixed effects also control for any time-invariant, firm-level productivity differences. Although our theoretical framework treats $X_i$ as stationary, empirically, it may not be. Adding, time varying $\text{Imp}_{im}$ accounts for this. Previous studies report that at Reunification the physical productivity (which we do not observe) of Eastern plants was at most 50 percent of comparable Western manufacturing plants' (Fritsch and Mallok, 1998). However, by the time our Eastern sample starts in 1992 the lowest productivity plants had already exited. Also, East German firms, though relatively well endowed compared to firms in other communist countries, had outdated capital equipment and despite a high level of formal education, employee skills did not suit a modern market economy and its division of labor (Fritsch and Mallok, 1998). In any case, differences in the productivity of firms, whether between East and West or simply across the street, should not obviously lead to differences in forecast quality, since these idiosyncratic firm capabilities are well-known within each firm making their own forecasts.

Convergence might also correlate with unobserved market uncertainty, if industries more dominated by Eastern firms became more predictable over time. Year-month-industry fixed effects ($\delta_{mj}$) absorb this uncertainty. These effects also absorb all other

[10]Every quarter the Business Expectations Survey also ask firms whether their production is impaired (yes/no) by any of the following: lack of orders, lack of manpower, lack of materials, lack of technical capacity, lack of finance and other impediments. The survey also asks about weather as an impediment which we exclude. Between 1992 and 2000 the question was asked monthly for Eastern firms. For other years and for Western firms we assume the variable is constant within quarters.

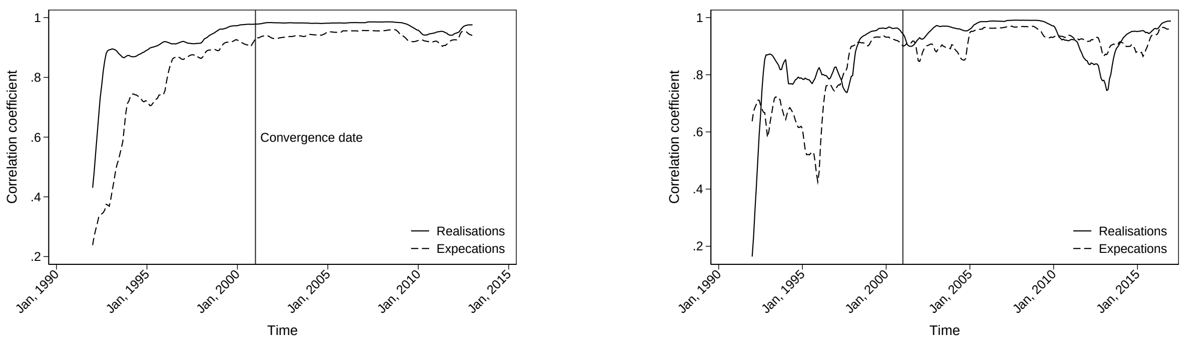
year-month-industry unobservables, including degree of competition, input and output price levels. We drop month-industry cells with less than 30 firm-level survey responses. An error term $\epsilon_{ijm}$, clustered at the firm level, captures any unobserved surprises in forecasting the industry business condition. Our estimator is the high dimension fixed effects estimator of Correia (2017).

Despite our control variables, one might worry that Reunification left Eastern firms not only with different understandings of the market than Western ones but different market conditions altogether. Here, we provide evidence that Eastern and Western firms operated in a common market after reunification and that therefore, the differences in forecast errors we identify stem from differences in expectations not realizations.

First, previous research suggests that after Reunification Eastern firms did not sell into different markets than Western firms. Hitchens et al. (1993, p. 34) show that Eastern firms swiftly reoriented their exports from planned to market economies.[11] After 1990 most transition countries underwent severe recessions and demand for East German firms' products collapsed. Furthermore, these countries suddenly had to pay for their imports from former East Germany in Deutschmarks, which they could not afford. In 1991 sales to former West Germany roughly doubled, while sales to Eastern Europe and the former USSR roughly halved. In any case, Hitchens *et al.* show that around Reunification just under 60 percent of Eastern firms' sales were domestic. For a different sample, Mallok (1996, p. 132) shows that only 7 per cent of East German firms' revenue came from exports to Eastern Europe in 1987. By 1992 the number had fallen to 1.6 per cent. For one of our robustness tests we also restrict our sample to exporting firms only as global market conditions were certainly the same for firms in East and West.

Second, our data itself indicates no substantial difference between the two regions' market states. Figure 3 plots the time series for the Pearson correlation coefficients between Eastern and Western aggregate realizations and expectations respectively (using 8 or 4 year rolling windows). The correlation between Eastern and Western aggregate realizations (solid line) rises rapidly above 0.8 almost immediately after Reunification and increases only slightly thereafter. Correlations between aggregate expectations (dashed line) reach similar strength only after 1997. The vertical line at year 2001 indicates

[11] This result is based on a survey of 32 firms in the East and 34 firms in the West in 1991 from the engineering, furniture, clothing, food, and misc. industry categories.




**(a)** 8 year window

**(b)** 4 year window

**Figure 3:** Components of the Market State Forecast Error

*Notes*: In this graph the lines plot the rolling correlation coefficients (8 and 4 year windows) between East and West. The solid line is for aggregate realizations and the dashed line is for aggregate expectations. The vertical line indicates the year that the predicted forecast errors for East and West are no longer statistically different.

the date when, according to our coefficient estimates below, Eastern forecast errors are no longer significantly higher than Western errors. This suggests that markets between regions homogenized quickly, and the slower convergence in forecast errors, which we find in our subsequent regressions, does not come from alignment of actual market conditions but rather expectations.

# 5. Results

Table 1 reports the regression results for the evolution of forecast errors after Reunification and, as we argue, Eastern firms are treated with a new market state generating process or, alternatively, ignorance. Column (1) gives the coefficient estimates for our baseline model (only controlling for industry-year-month fixed effects). The estimates support the predictions from our framework: Eastern firms, treated with market ignorance, forecast worse. But with the passage of time Eastern firms approach Western firms' forecast errors, at a diminishing rate. Although, as one would expect, the magnitudes of the coefficients vary with the subsample of firms and metric for measuring error, their signs are stable. The size of the coefficients is difficult to interpret and we only use them to estimate time to convergence, which is quantitatively robust across specifications, as shown below.

As convergence could be due to convergence in idiosyncratic firm conditions, Column (2), and all subsequent models, adds a time varying indicator for firms' self-reported impairment (Imp), a proxy for current internal firm state. The coefficient on East is lower, which is consistent with speculation that Eastern firms' internal conditions are less predictable immediately following Reunification, but the qualitative pattern in the coefficients of convergence does not change. As forecast error convergence could correlate with unobserved firm effects, e.g. variance in idiosyncratic firm states, productivity levels or management ability, we add firm fixed effects (dropping the time-invariant East indicator) in Column (3). Again the pattern in the coefficients reflecting convergence is the same, although absolute magnitude of the learning is lower, consistent with an expected positive correlation between learning and unobserved firm heterogeneity.

Our framework describes changes in mean squared error, but to ensure that our results are not an artifact of the magnification of large errors through squaring, Column (4) displays qualitatively similar results from a model using absolute value instead. Also, we show in Appendix C that our qualitative results are robust to more lenient or stringent error thresholds (see Section 3) as well as a binary error measure. Finally, Column (5) calculates the forecast error using a survey question that asks about expectations for own domestic production (*inländische Produktionstätigkeit*) rather than state of business.[12] Quantitatively, the East indicator is not comparable but again the signs for the convergence coefficients are stable.

[12]Like for the business condition question, the answers are qualitative and trichotomous. The method for calculating forecast errors is different from the one described above and is available upon request.

**Table 1:** Learning after Reunification

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| East (==1) | 0.413475*** | 0.367181*** | (*dropped*) | 0.190144*** | 0.127141*** |
| | [0.029] | [0.029] | | [0.016] | [0.016] |
| Trend × East | −0.107396*** | −0.094389*** | −0.044035** | −0.043672*** | −0.027844** |
| | [0.014] | [0.014] | [0.016] | [0.009] | [0.009] |
| $\text{Trend}^2 \times$ East | 0.009621*** | 0.008178*** | 0.002487 | 0.003228* | 0.002733* |
| | [0.002] | [0.002] | [0.002] | [0.001] | [0.001] |
| $\text{Trend}^3 \times$ East | −0.000336** | −0.000271* | −0.000010 | −0.000081 | −0.000122 |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] |
| $\text{Trend}^4 \times$ East | 0.000004 | 0.000003 | −0.000001 | 0.000000 | 0.000002 |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] |
| Firm impaired (Imp==1) | | 0.124193*** | 0.093874*** | 0.076445*** | 0.106243*** |
| | | [0.005] | [0.004] | [0.003] | [0.003] |
| Constant | 0.663647*** | 0.618013*** | 0.655169*** | 0.528700*** | 0.415012*** |
| | [0.003] | [0.004] | [0.004] | [0.003] | [0.003] |
| N | 1339885 | 1328989 | 1328457 | 1328989 | 1331056 |
| DV Mean | 0.67 | 0.67 | 0.67 | 0.56 | 0.46 |
| Firm FE | | | ✓ | | |
| Industry-Year-Month FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.0195 | 0.0234 | 0.1010 | 0.0229 | 0.0429 |

Standard errors in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes*: The dependent variable (DV) is the squared forecast error. (1) is our base model. (2) adds an indicator for firm impairment. (3) adds firm fixed effects. (4) uses the absolute error as the dependent variables. (5) uses survey question on own quantity to calculate forecast error. Standard errors are clustered at the firm level.

In Table 2 we report coefficient estimates using different sample restrictions imposed on the model in Column (2), Table 1. In our unbalanced sample, fixed effects control for firm heterogeneity but do not control for the fact that Eastern firms that exit early after Reunification might learn poorly. Therefore, in Column (1) we restrict our sample in the East to firms that answered the survey at least once before 1993 and once after 1999, which eliminates about 75 percent of Eastern firms. Recall that we do not actually observe market exit but only whether firms stop answering the survey, which certainly overestimates market exit. Since we assume that the average Western firm has learned capitalism, we do not similarly restrict the Western sample. Indeed, compared to Column (2) in Table 1, this sub-sample of Eastern firms initially has lower forecast errors, indicating that our baseline effect is a mixture of selection and learning by survivors.

Above we have given several pieces of evidence that suggest that, as in our theory, after reunification firms from both regions operate in the same market. To provide further evidence, Column (2) restricts the sample to exporting firms as exporting markets are likely to be identical after reunification, and convergence in market states or consumer tastes would largely be ruled out as a mechanism. Again, the results are qualitatively similar, but initially Eastern exporters make larger errors, suggesting that the ignorance treatment on Eastern firms is relatively bigger for the global than the domestic market. That the global market is more difficult to learn is also shown by a comparison with Column (3), which restricts the sample to non-exporters. The initial impact for non-exporters is much lower.[13] These results also make it unlikely that our results are primarily driven by new Western owners of Eastern firms learning the Eastern market. Certainly, for exporting firms, Western managers in Eastern firms would not make larger errors. Also, the greater initial errors and subsequent learning rate for Eastern firms that export beyond German borders suggests that the behavior of East German consumers does not primarily drive our results.

Instead of restricting the sample to exporters and non-exporters, Column (4) restricts the sample to intermediate goods producers (remember our sample is for manufacturing firms only).[14] If at all, these firms are impacted by changes in consumer tastes only indi-

[13]The finding that exporters make larger errors is consistent with the learning-by-exporting literature (e.g. Loecker, 2013).

[14]We define a manufacturing sector as "intermediate" for the following 2 and 3 digit sectors based on the WZ (2008) classification: 201, 202, 203, 211, 231, 251, 251, 253, 255, 256, 261, 271, 272, 273, 281,

rectly. Initially, these firms make larger errors. There are several possible explanations. Intermediate goods probably sell into larger and more global markets. Also, intermediate goods producers receive more noisy signals as they are located further up the supply chain. But again, the convergence results are robust. Finally, our results are also robust to the possibility that firms choose neutral survey responses due to laziness or rational inattention. We create an indicator that takes the value one if in a given month the firm's expectation and assessment are neutral. Table B.4 in Appendix B gives the coefficient estimates for a linear probability model where this indicator is a function of several firm characteristics. Not controlling for firm fixed effects, firms are more likely to give neutral answers the longer they have been responding to the Ifo survey and the larger they are (as measured by number of employees). However, once we control for firm fixed effects only self-reported impairment, which is already included in our models, affects the likelihood of a neutral response. In any case, Column (5) restricts the sample to observations that have non-neutral expectations and assessments. As we would expect, attentive firms in the East initially make larger errors.

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284, 289, 24.

**Table 2:** Learning after Reunification (different sample restrictions)

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| East (==1) | 0.196234*** | 0.501891*** | 0.251780*** | 0.497161*** | 0.918124*** |
| | [0.055] | [0.043] | [0.042] | [0.055] | [0.078] |
| Trend × East | −0.043921 | −0.129697*** | −0.057702** | −0.132868*** | −0.257939*** |
| | [0.026] | [0.020] | [0.022] | [0.028] | [0.042] |
| $\text{Trend}^2 \times$ East | 0.001962 | 0.011472*** | 0.004606 | 0.012118** | 0.022066*** |
| | [0.004] | [0.003] | [0.003] | [0.004] | [0.006] |
| $\text{Trend}^3 \times$ East | 0.000050 | −0.000397* | −0.000140 | −0.000449* | −0.000722* |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] |
| $\text{Trend}^4 \times$ East | −0.000003 | 0.000005 | 0.000001 | 0.000006 | 0.000008 |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] |
| Firm impaired (==1) | 0.123397*** | 0.125395*** | 0.120974*** | 0.111970*** | −0.011870 |
| | [0.005] | [0.006] | [0.009] | [0.009] | [0.014] |
| Constant | 0.617392*** | 0.624047*** | 0.598321*** | 0.647718*** | 0.960865*** |
| | [0.004] | [0.004] | [0.007] | [0.007] | [0.011] |
| N | 1227298 | 997534 | 324939 | 352220 | 261407 |
| DV Mean | 0.66 | 0.68 | 0.66 | 0.71 | 0.97 |
| Firm FE | | | | | |
| Industry-Year-Month FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.0222 | 0.0261 | 0.0500 | 0.0263 | 0.0684 |

Standard errors in brackets

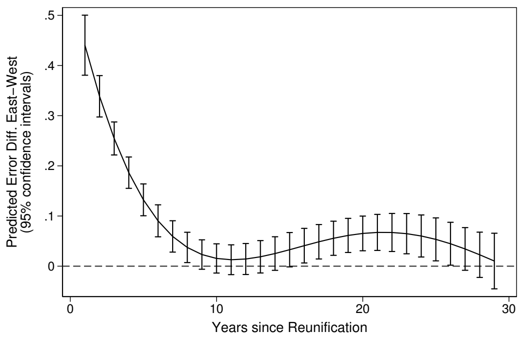
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes*: The dependent variable (DV) is the squared forecast error. (1) restricts the Eastern sample to firms that survived the period 1993 to 1999. (2) restricts the sample to exporters. (3) restricts the sample to non-exporters. (4) restricts the sample to intermediate goods producers. (5) restricts the sample to non-neutral expectations/realizations. Standard errors are clustered at the firm level.

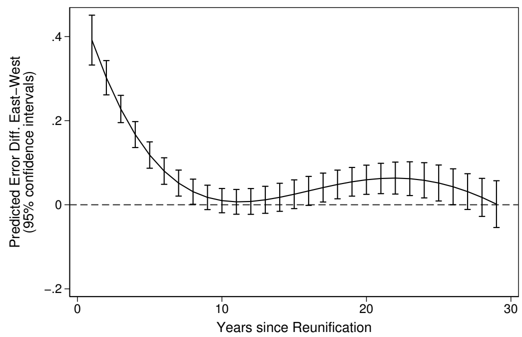
Firms learn to forecast business conditions, but how long did it take Eastern firms to forecast as accurately as their Western peers? The coefficient estimates let us predict the date. To do so we predict Eastern and Western firms' average forecast errors at discrete points in time at the sample mean of all other covariates.[15] Figure 4 plots the predicted forecast error differences between between East and West and their 95 percent confidence intervals for years after 1992 for various models. The top row is for the models in Column (1) and Column (2) in Table 1. The bottom-left panel has the firm fixed effects model in Column (3) and the bottom-right has a model that uses a binary forecast error (see Appendix C). Visual inspection of the confidence intervals shows that for all models, except that with firm fixed effects, convergence occurs after nine years, in 2001. More precisely, only after nine years do we fail to reject the null hypothesis that the difference between Eastern and Western forecast error magnitudes is zero at a 95 percent significance level. The coefficients of the firm fixed effects model have much wider confidence intervals and, hence, although its point estimates do not converge faster, the difference in predicted forecast errors between Eastern and Western firms is no longer statistically significant after seven years. So, while the individual coefficients of our various specifications adjust from model to model, they do so in concert, such that our main result that it took Eastern firms nine years to learn to forecast the market as well as their Western peers is quantitatively robust. Using that convergence took nine years, the coefficient estimates yield a constant learning rate of about five percent per annum.[16]

[15] Our counterfactual analysis treats all observations as either Eastern or Western, *e.g.* all observations that are actually Western are also fitted assuming they were Eastern.

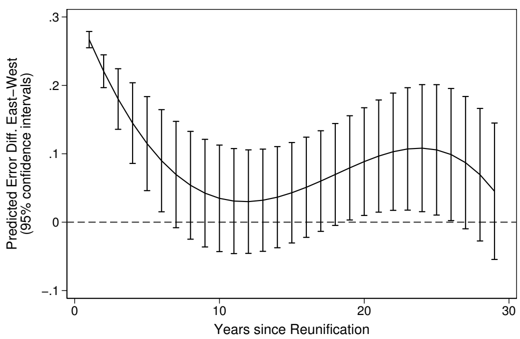
[16] Annual learning rate $r$ solves $E_{i \in East}[MSE_{i0}](1-r)^T = E_{j \in West}[MSE_{j\infty}]$, where $T$ is the years to convergence, and $MSE_{it}$ is defined in Section 2. Drawing the coefficients from our preferred model in Table 1, Column 1. $E_{j \in West}[MSE_{j\infty}] = 0.62$,which is the average Western forecast error, $E_{i \in East}[MSE_{i0}] = 0.62 + 0.37$, and $T = 9$. Hence, $r = 0.05$.



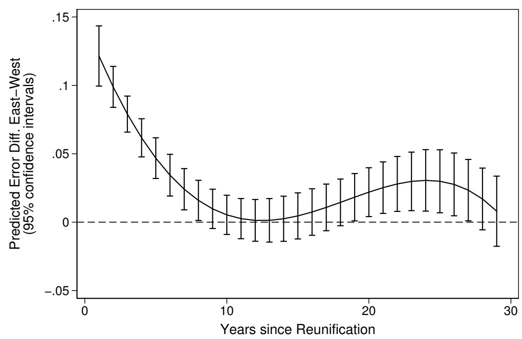

**(a)** Industry-Month Fixed Effects




**(b)** Impairment Indicator




**(c)** Firm Fixed Effects




**(d)** Binary Forecast Error

**Figure 4:** Forecast Error Convergence

*Notes*: This graph plots the predicted difference in forecast error magnitude between East and West and its 95% confidence interval.

# 6. Conclusion

Many economic theories hinge on market actors being able to predict future market characteristics. For nearly forty years, learning has been offered as a theoretical justification for the dominant paradigm to describe expectation formation: *rational expectations*. By comparing firms in former East and West Germany that survived the Reunification of Germany, we can test whether Eastern firms learn how to predict market states after structural shocks to the economy. They do. When time from Reunification proxies for experience, we find empirical support for all the predictions of our Bayesian learning framework. Of particular importance, forecast quality between Eastern and Western firms converges, after roughly a decade. Our evidence suggests that this delay is not due to slow convergence of the markets themselves, as these align quickly but due to gradual improvement in predictions by Eastern firms.

Our study is not without limitations. Although we measure the learning of Eastern firms that live through Reunification,, we cannot ultimately disentangle *organizational learning* from *individual learning*. Although we have ruled out survival of the fittest at the firm level as the sole driver of the observed improvements, we cannot rule out that better forecasting managers (many Eastern firms replaced top management with Westerners) displace worse ones within firms.

Our conclusion is twofold: (1) in addition to the omnipresent sources of uncertainty, like volatility and signal noise, that complicate firms' day-to-day forecasting, structural economic changes also disrupt firms' fundamental understanding of the market, (2) and learning how it works takes years, about nine in the case of German Reunification. This finding suggests institution building and major policy enactment, whether as a result of redrawing political boundaries, nation building, a dramatic response to climate change or a pandemic, must be accompanied by patience. Preserving firms and their institutional knowledge in the face of severe temporary shocks may also improve productivity when conditions return to normal. Economic agents find their way...eventually.

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# A. Proof of Hypotheses Under Normality Assumptions

Formally proving the hypotheses presented in Section 2 requires additional structure. Here, we prove them under an often used set of assumptions, but others would generate qualitatively similar results. Let the distribution $G$ of the market state $Y_t$ be $Normal\left(\mu_Y, \sigma_Y^2\right)$. That is, following the notation of Section 2, $\mathbf{z} = \langle \mu_Y, \sigma_Y^2 \rangle$, $\mu_Y[\mathbf{z}] = \mathbf{z}_1$ and $\sigma_Y^2[\mathbf{z}] = \mathbf{z}_2$. Let signal noise $\varepsilon_{it}$ be distributed $Normal\left(0, \sigma_\varepsilon^2\right)$ for all firms. For simplicity, assume firms know the value of $\sigma_Y^2$ but not $\mu_Y$; they must learn it. Firm $i$ holds normally distributed prior beliefs $\mu_{iY0}$ with prior variance $\sigma_{iY0}^2$ about the mean of the market state variable $\mu_Y$, but these beliefs are updated over time. In the notation of Section 2, $\hat{\mathbf{z}}_{it} = \langle \mathbf{z}_{1t}, \mathbf{z}_{2t} \rangle$, where $\hat{\mathbf{z}}_{2t}$ is Dirac at $\sigma_Y^2$ for all $t$, and $\hat{\mathbf{z}}_{10}$ is a univariate $Normal\left(\mu_{iY0}, \sigma_{iY0}^2\right)$ distribution. The distribution $\hat{\mathbf{z}}_{1t}$ is updated as described below.

Let us begin by considering how the firm learns the mean of the market state DGP, $\mu_Y$. First note that although the firm depends critically on its market signal $\hat{Y}_{it}$ to forecast the market state $Y_t$, the true state is fully revealed to the firm at the end of the period, and thus the signal plays no direct role in the learning. It is well known that the posterior predictive distribution of $Y_t$, normally distributed with unknown mean and variance $\sigma_Y^2$, *unconditional on the market signal* is $Normal\left(\mu_{iYt}, \sigma_{iYt}^2 + \sigma_Y^2\right)$ where

$$\begin{aligned} \mu_{iYt} &= \frac{\sigma_Y^2}{t\sigma_{iY0}^2 + \sigma_Y^2}\mu_{i0} + \frac{t\sigma_{iY0}^2}{t\sigma_{iY0}^2 + \sigma_Y^2}\bar{Y}_t \\ \sigma_{iYt}^2 &= \frac{\sigma_{iY0}^2\sigma_Y^2}{t\sigma_{iY0}^2 + \sigma_Y^2} \end{aligned} \tag{4}$$

and $\bar{Y}_t$ is the sample mean of realized market states up to time $t$.[17, 18] The firm's understanding of the learned parameter $\mu_Y$, then is normally distributed with mean $\mu_{iYt}$ and variance $\sigma_{iYt}^2 + \sigma_Y^2$. Intuitively the firm's understanding, or best guess for the mean of the market state distribution $\mu_{iYt}$, is comprised of a weighting of the initial prior $\mu_{i0}$ and the average of the realized observations up to the current time $\bar{Y}_t$—with more experience ($t \to \infty$) all of the weight shifts from the prior to the sample average of realized observations. From the perspective of a forecaster, who does not know the true market

[17] The posterior predictive distribution is the is the distribution of unobserved observations, conditional on the observed data.

[18] See https://www.cs.ubc.ca/~murphyk/Papers/bayesGauss.pdf for a derivation.

state distribution, variance in realizations comes both from the ordinary volatility in the market state captured by $\sigma_Y^2$ and uncertainty in understanding $\sigma_{iYt}^2$. This latter source of variance vanishes as the forecaster learns the model—all that remains is the market volatility.

Now let us turn to the role of these market features on the firm's *internal* predictions about the market state *conditional on the market signal.*[19] Conditional on having observed market signal $\hat{Y}_{it}$ (and the entire history of state realizations $\Omega_{it}$) the posterior predictive of $Y_t$ is well-known to be normally distributed with mean and variance

$$E\left[Y_t|\,\hat{Y}_{it},\Omega_{it}\right] = w_m\mu_{iYt} + w_s\hat{Y}_{it} \tag{5}$$

$$Var\left[Y_t|\,\hat{Y}_{it},\Omega_{it}\right] = \frac{\left(\sigma_{iYt}^2+\sigma_Y^2\right)\sigma_\varepsilon^2}{\left(\sigma_{iYt}^2+\sigma_Y^2\right)+\sigma_\varepsilon^2} \tag{6}$$

where the informational weight placed on the *expected* market state mean $w_m$ and the informational weight placed on the signal $w_s$ are respectively given by

$$w_m = \frac{\sigma_\varepsilon^2}{\left(\sigma_{iYt}^2+\sigma_Y^2\right)+\sigma_\varepsilon^2} \text{ and } w_s = \frac{\sigma_{iYt}^2+\sigma_Y^2}{\left(\sigma_{iYt}^2+\sigma_Y^2\right)+\sigma_\varepsilon^2}. \tag{7}$$

Using the above results, we can prove the hypotheses of Section 2.

**Hypothesis (i)** *Assuming the average variance in idiosyncratic firm states is at least as high in the East as in the West (i.e.* $E_i\left[\sigma_{Xi}^2\right] \geq E_j\left[\sigma_{Xj}^2\right], i \in East, j \in West$*), then immediately following Reunification, average forecast error magnitude in the East exceeds the average forecast error magnitude in the West (*$E_i\left[MSE_{i0}\right] \geq E_j\left[MSE_{j\infty}\right], i \in East, j \in West$*).*

*Proof.* From (1) $E_i\left[MSE_{i0}\right] \geq E_j\left[MSE_{j\infty}\right]$ holds if and only if

$$E_i\left[\sigma_{Xi}^2\right] + E_i\left[Var\left[Y_0|\,\hat{Y}_{i0},\Omega_{it}\right]\right] \geq E_j\left[\sigma_{Xj}^2\right] + E_j\left[Var\left[Y_\infty|\,\hat{Y}_{j\infty},\Omega_{j\infty}\right]\right]$$

Substituting in (6) this condition becomes

$$E_i\left[\sigma_{Xi}^2\right] + E_i\left[\frac{\left(\sigma_{iY0}^2+\sigma_Y^2\right)\sigma_\varepsilon^2}{\left(\sigma_{iY0}^2+\sigma_Y^2\right)+\sigma_\varepsilon^2}\right] \geq E_j\left[\sigma_{Xj}^2\right] + E_j\left[\frac{\left(\sigma_{iY\infty}^2+\sigma_Y^2\right)\sigma_\varepsilon^2}{\left(\sigma_{iY\infty}^2+\sigma_Y^2\right)+\sigma_\varepsilon^2}\right]$$

[19] Recall that the firm, although it observes the market state $Y_t$, reports its firm-specific state of business (lit. *Geschäftslage*) $S_{it} = X_{it} + Y_t$.

Substituting in (4), it can be written

$$E_i\left[\sigma_{Xi}^2\right]+E_i\left[\left.\frac{\left(\frac{\sigma_{iY0}^2\sigma_Y^2}{t\sigma_{iY0}^2+\sigma_Y^2}+\sigma_Y^2\right)\sigma_\varepsilon^2}{\left(\frac{\sigma_{iY0}^2\sigma_Y^2}{t\sigma_{iY0}^2+\sigma_Y^2}+\sigma_Y^2\right)+\sigma_\varepsilon^2}\right|_{t=0}\right]\geq E_j\left[\sigma_{Xj}^2\right]+E_j\left[\lim_{t\to\infty}\frac{\left(\frac{\sigma_{iY0}^2\sigma_Y^2}{t\sigma_{iY0}^2+\sigma_Y^2}+\sigma_Y^2\right)\sigma_\varepsilon^2}{\left(\frac{\sigma_{iY0}^2\sigma_Y^2}{t\sigma_{iY0}^2+\sigma_Y^2}+\sigma_Y^2\right)+\sigma_\varepsilon^2}\right]$$

Simplifying, $E_i\left[MSE_{i0}\right]\geq E_j\left[MSE_{j\infty}\right]$ holds if and only if

$$E_i\left[\sigma_{Xi}^2\right]+E_i\left[\frac{\left(\sigma_{iY0}^2+\sigma_Y^2\right)\sigma_\varepsilon^2}{\left(\sigma_{iY0}^2+\sigma_Y^2\right)+\sigma_\varepsilon^2}\right]\geq E_j\left[\sigma_{Xj}^2\right]+\frac{\sigma_Y^2\sigma_\varepsilon^2}{\sigma_Y^2+\sigma_\varepsilon^2}$$

which is true, because $E_i\left[\sigma_{Xi}^2\right]\geq E_j\left[\sigma_{Xj}^2\right]$, $\frac{d}{dx}\frac{xy}{x+y}=\frac{y^2}{(x+y)^2}>0$, and $\sigma_{iY0}^2>0$. □

**Hypothesis (ii)** *Average forecast error magnitude in the East declines with experience ($\frac{d}{dt}E_i\left[MSE_{it}\right]<0, i\in East$).*

*Proof.* First observe, from (4), that understanding increases over time:

$$\frac{d\sigma_{iYt}^2}{dt}=-\sigma_Y^2\left(\frac{\sigma_{iY0}^2}{t\sigma_{iY0}^2+\sigma_Y^2}\right)^2=-\frac{\left(\sigma_{iYt}^2\right)^2}{\sigma_Y^2}<0 \tag{8}$$

From (1), and (6)

$$\frac{d}{dt}E_i\left[MSE_{it}\right]=E_i\left[\frac{d}{dt}\frac{\left(\sigma_{iYt}^2+\sigma_Y^2\right)\sigma_\varepsilon^2}{\left(\sigma_{iYt}^2+\sigma_Y^2\right)+\sigma_\varepsilon^2}\right]=E_i\left[\left(\frac{\sigma_\varepsilon^2}{\sigma_{iYt}^2+\sigma_Y^2+\sigma_\varepsilon^2}\right)^2\frac{d}{dt}\sigma_{iYt}^2\right]<0 \tag{9}$$

□

**Hypothesis (iii)** *The average rate of forecast error reduction slows with experience ($\frac{d^2}{dt^2}E_i\left[MSE_{it}\right]>0, i\in East$).*

*Proof.* Observe, from (8), that the rate of understanding improvement slows over time:

$$\frac{d^2\sigma_{iYt}^2}{dt^2}=2\frac{\left(\sigma_{iYt}^2\right)^3}{\left(\sigma_Y^2\right)^2}=\frac{2}{\sigma_{iYt}^2}\left(-\frac{\left(\sigma_{iYt}^2\right)^2}{\sigma_Y^2}\right)^2=\frac{2}{\sigma_{iYt}^2}\left(\frac{d\sigma_{iYt}^2}{dt}\right)^2>0 \tag{10}$$

From (9)

$$
\begin{aligned}
\frac{d^2}{dt^2}E_i\left[MSE_{it}\right] &= \frac{d}{dt}E_i\left[\left(\frac{\sigma_\varepsilon^2}{\sigma_{iYt}^2+\sigma_Y^2+\sigma_\varepsilon^2}\right)^2\frac{d}{dt}\sigma_{iYt}^2\right] \\
&= E_i\left[-2\frac{\left(\sigma_\varepsilon^2\right)^2}{\left(\sigma_{iYt}^2+\sigma_Y^2+\sigma_\varepsilon^2\right)^3}\left(\frac{d\sigma_{iYt}^2}{dt}\right)^2+\left(\frac{\sigma_\varepsilon^2}{\sigma_{iYt}^2+\sigma_Y^2+\sigma_\varepsilon^2}\right)^2\frac{d^2\sigma_{iYt}^2}{dt^2}\right] \\
&= E_i\left[2\left(\frac{\sigma_\varepsilon^2}{\sigma_{iYt}^2+\sigma_Y^2+\sigma_\varepsilon^2}\right)^2\left(\frac{1}{\sigma_{iYt}^2}-\frac{1}{\sigma_{iYt}^2+\sigma_Y^2+\sigma_\varepsilon^2}\right)\left(\frac{d\sigma_{iYt}^2}{dt}\right)^2\right]>0
\end{aligned}
$$

□

**Hypothesis (iv)** *Assuming the average variance in idiosyncratic firm states in the East equals those in the West (i.e.* $E_i\left[\sigma_{Xi}^2\right]=E_j\left[\sigma_{Xj}^2\right], i\in East, j\in West$*), then average forecast error magnitude in the East converges to the average forecast error magnitude in the West (*$\lim_{t\to\infty}E_i\left[MSE_{it}\right]=E_j\left[MSE_{j\infty}\right], i\in East, j\in West$*).*

*Proof.* From (1), and (6)

$$
\lim_{t\to\infty}E_i\left[MSE_{it}\right]=E_i\left[\sigma_{Xi}^2\right]+E_i\left[\lim_{t\to\infty}\frac{\left(\sigma_{iYt}^2+\sigma_Y^2\right)\sigma_\varepsilon^2}{\left(\sigma_{iYt}^2+\sigma_Y^2\right)+\sigma_\varepsilon^2}\right]=E_i\left[\sigma_{Xi}^2\right]+\frac{\sigma_Y^2\sigma_\varepsilon^2}{\sigma_Y^2+\sigma_\varepsilon^2}=E_j\left[MSE_{jt}\right]
$$

where we have used that $\lim_{t\to\infty}\sigma_{iYt}^2=0$ and $E_i\left[\sigma_{Xi}^2\right]=E_j\left[\sigma_{Xj}^2\right]$. □

# B. Forecast Quality

Given that survey responses are subjective and qualitative we verify their quality. Our argument that forecast error convergence captures firm learning requires that firm behavior is consistent with forecasts. For instance, forecasts would be uninformative and convergence might be spurious if firms blindly repeated forecasts or used the current business state realization as their forecast. We use a number of empirical models to assess the quality of our data. The following models are estimated with standard errors robust to unknown time-series and cross-sectional dependence (Driscoll and Kraay, 1998).

Table B.1 shows that firms do not simply repeat forecasts. Even for our monthly forecasts, the autocorrelation coefficient for forecasts is well below 1 and controlling for firm and time fixed effects in Column (3), the coefficient is below 0.5. Table B.2 shows that the autocorrelation for the forecast error is slightly higher, which is consistent with

**Table B.1:** Autocorrelation of Forecasts

| | (1) | (2) | (3) |
|---|---|---|---|
| Forecast (t-1) | 0.5688*** | 0.5462*** | 0.4490*** |
| | [0.004] | [0.003] | [0.003] |
| Constant | −0.0194** | 0.0195*** | −0.0308*** |
| | [0.007] | [0.000] | [0.002] |
| N | 1250029 | 1250029 | 1250029 |
| DV Mean | −0.04 | −0.04 | −0.04 |
| Firm FE | | | ✓ |
| Month-Year FE | | ✓ | ✓ |
| $R^2$ | 0.3239 | 0.3380 | |

Standard errors in brackets
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes*: The dependent variable is the forecast and the independent variable is the one month lagged forecast. Driscoll-Kraay standard errors with lag 5 are shown in parentheses.

the literature that shows that expectation formation follows an error correction model (e.g. Nerlove, 1983). Table B.3 provides evidence that firms do not simply forecast the current state of business. Controlling for firm and time effects the correlation between forecasts and the current state of business below is 0.2.

**Table B.2:** Autocorrelation of Forecast Errors

| | (1) | (2) | (3) |
|---|---|---|---|
| Forecast error (t-1) | 0.6062*** | 0.5927*** | 0.5189*** |
| | [0.004] | [0.003] | [0.003] |
| Constant | 0.0036 | 0.1280*** | 0.0653*** |
| | [0.007] | [0.001] | [0.004] |
| N | 1238751 | 1238751 | 1238751 |
| DV Mean | 0.01 | 0.01 | 0.01 |
| Product FE | | | ✓ |
| Month-Year FE | | ✓ | ✓ |
| $R^2$ | 0.3662 | 0.3746 | |

Standard errors in brackets
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes*: The dependent variable is the forecast and the independent variable is the one month lagged forecast. Driscoll-Kraay standard errors with lag 5 are shown in parentheses.

Finally, as the majority of firm expectations is neutral, there is a worry that low forecast errors are an artifact of firms' laziness or inattention. To explore this we create an indicator that takes value 1 if reported expectation and realization are neutral. We then correlate the (linear) probability of neutral answers with the count of a firm's survey responses to date, firm size, exporter status, whether the firm self-reports any impairment

**Table B.3:** Forecast and Realization

| | (1) | (2) | (3) |
|---|---|---|---|
| Realization (t) | 0.2094*** | 0.1893*** | 0.1438*** |
| | [0.007] | [0.003] | [0.003] |
| Constant | −0.0372** | 0.0877*** | −0.0188*** |
| | [0.013] | [0.001] | [0.004] |
| N | 1367604 | 1367604 | 1367604 |
| DV Mean | −0.04 | −0.04 | −0.04 |
| Product FE | | | ✓ |
| Month-Year FE | | ✓ | ✓ |
| $R^2$ | 0.0551 | 0.0962 | |

Standard errors in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes*: The dependent variable is the forecast and the independent variable is the current realization. Driscoll-Kraay standard errors with lag 5 are shown in parentheses.

to production, industry-year-month fixed effects, and firm fixed effects for some models. The estimator is the high dimension fixed effects estimator of Correia (2017). Table B.4 gives the coefficient estimates separate for East and West and for models with and without firm fixed effects. The bottom of the table shows that, unconditionally, Western and Eastern firms give 66 and 61 per cent of neutral answers, respectively.

Consistent with our view that the reported state of business encompasses a firm-specific component, firms reporting impairements to production give fewer neutral forecasts in both regions even when including firm fixed effects. Excluding firm fixed effects, there is evidence that for both regions the probability of neutral answers increases with the length a firm has been responding to the survey and firm size. Not exporting also increases the probability for Eastern firms. These results give support to the rational inattention hypothesis and justify the exclusion of neutral answers as a robustness test above.

**Table B.4:** Determinants of Neutral Answers

| | (1) West | (2) East | (3) West | (4) East |
|---|---|---|---|---|
| Survey responses | 0.0003*** | 0.0005*** | 0.0004* | −0.0002 |
| | [0.000] | [0.000] | [0.000] | [0.000] |
| log(Production Employees) | 0.0078*** | 0.0168** | 0.0020 | 0.0110 |
| | [0.002] | [0.006] | [0.004] | [0.010] |
| Exporter (==1) | 0.0097 | −0.0389* | 0.0070 | 0.0056 |
| | [0.007] | [0.017] | [0.009] | [0.014] |
| Firm Impaired (==1) | −0.2458*** | −0.1350*** | −0.1985*** | −0.0934*** |
| | [0.004] | [0.012] | [0.003] | [0.009] |
| Constant | 0.6628*** | 0.5884*** | 0.6575*** | 0.6165*** |
| | [0.010] | [0.027] | [0.033] | [0.046] |
| N | 673622 | 86304 | 673390 | 85946 |
| DV Mean | 0.66 | 0.61 | 0.66 | 0.61 |
| Firm FE | | | ✓ | ✓ |
| Industry-Year-Month FE | ✓ | ✓ | ✓ | ✓ |

Standard errors in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes*: The dependent variable is an indicator that takes the value 1 if the firm gives a neutral expectation and realization for the market state. OLS regression.

Above, we showed that forecast errors are not spurious, but do they correlate to firm decisions? In the text we already showed that forecast errors relate to capacity utilization and inventory levels. Table B.5 shows that business condition forecasts also positively correlate with firm-level employment forecasts.[20] Firms' plans are consistent with their forecasts.

**Table B.5:** Business Condition and Employment Forecasts

| | (1) | (2) | (3) |
|---|---|---|---|
| Forecast employement | 0.3719*** | 0.3590*** | 0.3031*** |
| | [0.011] | [0.007] | [0.005] |
| Constant | 0.0173 | −0.6795*** | −0.8054*** |
| | [0.013] | [0.004] | [0.032] |
| N | 900532 | 900532 | 900532 |
| DV Mean | −0.02 | −0.02 | −0.02 |
| Firm FE | | | ✓ |
| Month-Year FE | | ✓ | ✓ |
| $R^2$ | 0.0833 | 0.1257 | |

Standard errors in brackets
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes*: The dependent variable is the business condition forecast and the independent variable is the firm-level employment forecast. Driscoll-Kraay standard errors with lag 5 are shown in parentheses.

In the introduction we show that directional forecast errors correlate with subjective profitability. But do firms' forecast error magnitudes also correlate with objective, accounting profitability? We measure profitability as either gross profit (loss) or cash flow divided by fixed assets.[21] Table B.6 gives the results for regressions of these profitability measures on last years average forecast error, firm size (measured by the log of employees, an indicator for whether the firm is an exporter, and industry-year-month effects. The latter should control for input and output prices, the arguments in the theoretical profit function. Some models also include firm fixed effects. The estimator is the high dimension fixed effects estimator of Correia (2017). Albeit statistically insignificant at the usual levels, there is a negative correlation between lagged forecast errors and profitability for almost all models. Also as expected the effect is larger for cash flow based profitability. This is the same result as found by Tanaka et al. (2020) in an entirely different context.

[20] The survey question for employment forecast reads as follows: *Expectations for the next three months: Employment (only domestic): The number of employees for the production of X will (1) increase, (0) stay the same, or (-1) decrease.*

[21] The data is from the ifo's Business Expectation Panel (BEP). This is a subset of the survey data used above matched with accounting data from Amadeus.

**Table B.6:** Forecasts errors and profitability

| | Gross profit/loss | | | Cash flow | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Forecast error (lag) | −14.9100 | −15.7308 | −16.4014 | −0.2755 | −0.3726 | 0.1350 |
| | [0.221] | [0.229] | [0.222] | [0.573] | [0.516] | [0.420] |
| ln(Labor) | | −12.7939 | −20.4920 | | −1.7343 | −0.3505* |
| | | [0.361] | [0.218] | | [0.249] | [0.045] |
| Exporter (==1) | | 45.0537 | 28.4182 | | 1.9388 | 3.2651 |
| | | [0.213] | [0.247] | | [0.356] | [0.365] |
| Constant | 41.0137 | 69.9223 | 125.8235 | 1.6756 | 10.0499 | −0.4579 |
| | [0.069] | [0.298] | [0.140] | [0.176] | [0.224] | [0.896] |
| N | 19442 | 18837 | 18454 | 14300 | 13721 | 13483 |
| DV Mean | 30.55 | 31.46 | 31.80 | 1.49 | 1.54 | 0.59 |
| Firm FE | | | ✓ | | | ✓ |
| Industry-Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.0088 | 0.0089 | 0.0804 | 0.0150 | 0.0154 | 0.3145 |

$p$-values in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes*: The dependent variable is gross profit (loss) or cash flow divided by fixed assets. Forecast error is the annual average of squared forecast errors.

In conclusion, our survey forecasts contain relevant information for our analysis, which is consistent with previous findings for the same and similar surveys (Massenot and Pettinicchi, 2018; Coibion et al., 2018; **?**).

# C. Different Error Definitions

In this section we test the robustness of our results to different definitions of the forecast error. First, we eliminate the distinction between small and large errors, that is we only differentiate between error (1) or no error (0). The regression results (equivalent to Table 1) are in Table C.1. As expected the coefficient estimate for East is lower, but time to convergence is unchanged (see Figure 4 in the text).

Second, we maintain the original distinction between small and large errors but change the parameterization as introduced in section 3. Recall that our preferred specification uses the following parameterization when calculating the errors: $H\left[good\right] = \frac{2}{3}$, $H\left[satisfactory\right] = \frac{1}{3}$ and $H\left[bad\right] = 0$. To test robustness to this parameterization we make the requirements to obtain an error more or less stringent. We make it harder to obtain a (large) error by defining: $H\left[good\right] = \frac{3}{4}$, $H\left[satisfactory\right] = \frac{1}{3}$ and $H\left[bad\right] = -\frac{1}{3}$ (Table C.2). And we can make it easier by defining: $H\left[good\right] = \frac{1}{2}$, $H\left[satisfactory\right] = \frac{1}{4}$ and $H\left[bad\right] = 0$ (Table C.3). Consistent with the stringency of the error definition the first order effect of East is lower (higher) in Table C.2 (in Table C.3) than in Table 1. Nevertheless, convergence still takes 9 years for both models.

**Table C.1:** Learning and Reunification (Binary Forecast Errors)

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| East (==1) | 0.121487*** | 0.101626*** | (*dropped*) | 0.101626*** | 0.046585*** |
| | [0.011] | [0.011] | | [0.011] | [0.009] |
| Trend × East | −0.023976*** | −0.018314** | −0.008900 | −0.018314** | −0.012110* |
| | [0.007] | [0.007] | [0.007] | [0.007] | [0.006] |
| $\text{Trend}^2 \times$ East | 0.001395 | 0.000752 | −0.000609 | 0.000752 | 0.001625 |
| | [0.001] | [0.001] | [0.001] | [0.001] | [0.001] |
| $\text{Trend}^3 \times$ East | −0.000015 | 0.000014 | 0.000085 | 0.000014 | −0.000087 |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] |
| $\text{Trend}^4 \times$ East | −0.000000 | −0.000001 | −0.000002 | −0.000001 | 0.000001 |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] |
| Firm impaired (Imp==1) | | 0.052571*** | 0.039332*** | 0.052571*** | 0.081532*** |
| | | [0.003] | [0.002] | [0.003] | [0.002] |
| Constant | 0.503320*** | 0.484043*** | 0.498763*** | 0.484043*** | 0.366113*** |
| | [0.002] | [0.002] | [0.002] | [0.002] | [0.002] |
| N | 1339885 | 1328989 | 1328457 | 1328989 | 1331056 |
| DV Mean | 0.51 | 0.51 | 0.51 | 0.51 | 0.40 |
| Firm FE | | | ✓ | | |
| Industry-Year-Month FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.0171 | 0.0196 | 0.0981 | 0.0196 | 0.0366 |

Standard errors in brackets
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes*: The dependent variable (DV) is the binary forecast error. (1) is our base model. (2) adds an indicator for firm impairment. (3) adds firm fixed effects. (4) uses the absolute error as the dependent variables. (5) uses survey question on own quantity to calculate forecast error. Standard errors are clustered at the firm level.

**Table C.2:** Learning and Reunification (Stringent Error Thresholds)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| East (==1) | 0.396489*** | 0.349353*** | (*dropped*) | 0.181024*** |
| | [0.028] | [0.028] | | [0.015] |
| Trend × East | −0.100351*** | −0.087157*** | −0.043878** | −0.040239*** |
| | [0.014] | [0.014] | [0.016] | [0.008] |
| $\text{Trend}^2 \times$ East | 0.009019*** | 0.007565*** | 0.002542 | 0.002955* |
| | [0.002] | [0.002] | [0.002] | [0.001] |
| $\text{Trend}^3 \times$ East | −0.000321** | −0.000256* | −0.000019 | −0.000076 |
| | [0.000] | [0.000] | [0.000] | [0.000] |
| $\text{Trend}^4 \times$ East | 0.000004* | 0.000003 | −0.000001 | 0.000000 |
| | [0.000] | [0.000] | [0.000] | [0.000] |
| Firm impaired (Imp==1) | | 0.126608*** | 0.097621*** | 0.077823*** |
| | | [0.005] | [0.004] | [0.003] |
| Constant | 0.686218*** | 0.639777*** | 0.676644*** | 0.539874*** |
| | [0.003] | [0.004] | [0.004] | [0.003] |
| N | 1339885 | 1328989 | 1328457 | 1328989 |
| DV Mean | 0.70 | 0.69 | 0.69 | 0.57 |
| Firm FE | | | ✓ | |
| Industry-Year-Month FE | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.0178 | 0.0216 | 0.0893 | 0.0214 |

Standard errors in brackets
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes*: The dependent variable (DV) is the squared forecast error using a stringent error definition. (1) is our base model. (2) adds an indicator for firm impairment. (3) adds firm fixed effects. (4) uses the absolute error as the dependent variables. Standard errors are clustered at the firm level.

**Table C.3:** Learning and Reunification (Relaxed Error Thresholds)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| East (==1) | 0.440455*** | 0.391663*** | (*dropped*) | 0.201403*** |
| | [0.031] | [0.030] | | [0.016] |
| Trend × East | −0.111355*** | −0.097517*** | −0.049036** | −0.044571*** |
| | [0.015] | [0.015] | [0.017] | [0.009] |
| $\text{Trend}^2 \times$ East | 0.009881*** | 0.008330*** | 0.002861 | 0.003194* |
| | [0.002] | [0.002] | [0.002] | [0.001] |
| $\text{Trend}^3 \times$ East | −0.000342** | −0.000271* | −0.000022 | −0.000075 |
| | [0.000] | [0.000] | [0.000] | [0.000] |
| $\text{Trend}^4 \times$ East | 0.000004 | 0.000003 | −0.000001 | 0.000000 |
| | [0.000] | [0.000] | [0.000] | [0.000] |
| Firm impaired (Imp==1) | | 0.130014*** | 0.100873*** | 0.076254*** |
| | | [0.005] | [0.004] | [0.003] |
| Constant | 0.695019*** | 0.647215*** | 0.687342*** | 0.548787*** |
| | [0.004] | [0.004] | [0.005] | [0.003] |
| N | 1339885 | 1328989 | 1328457 | 1328989 |
| DV Mean | 0.71 | 0.70 | 0.70 | 0.58 |
| Firm FE | | | ✓ | |
| Industry-Year-Month FE | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.0201 | 0.0241 | 0.1073 | 0.0235 |

Standard errors in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes*: The dependent variable (DV) is the squared forecast error using a relaxed error definition. (1) is our base model. (2) adds an indicator for firm impairment. (3) adds firm fixed effects. (4) uses the absolute error as the dependent variables. Standard errors are clustered at the firm level.