

## Online Appendix for

### “Changing Business Dynamism and Productivity: Shocks vs. Responsiveness”<sup>1</sup>

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#### Appendix I: Model framework

##### A. General formulation

Consider a class of models in which revenue of firm<sup>2</sup>  $j$  in time  $t$  is given by  $A_{jt}E_{jt}^\phi$ , where  $A_{jt}$  is a composite shock reflecting both technical efficiency and, potentially, demand shocks,  $E_{jt}$  is employment, and  $\phi < 1$  reflects revenue function curvature arising from imperfect competition due to, for example, product differentiation (related arguments go through for decreasing returns to scale). Suppose the shock  $A_{jt}$  follows the process  $\ln A_{jt} = \rho_a \ln A_{jt-1} + \eta_{jt}$ . This setup is common to a wide range of models of firm dynamics and typically gives rise to an employment growth policy function given by:

$$g_{jt} = f_t(A_{jt}, E_{jt-1}) \quad (\text{A1})$$

where  $g_{jt}$  is employment growth from  $t - 1$  to  $t$ ; this is the same as equation (1) in the main text. It is commonly the case that  $\frac{\partial f}{\partial A} > 0$ ; that is, for any two firms with the same employment, the firm with higher  $A$  has higher growth. For empirical purposes, (A1) leads to the following log-linear approximation:

$$g_{jt} = \beta_0 + \beta_1 a_{jt} + \beta_2 e_{jt-1} + \varepsilon_{jt} \quad (\text{A2})$$

While (A1) and its empirical counterpart (A2) are quite general, it is useful to illustrate the employment growth function using a special case of a simple model that is free of frictions or distortions (which we will add below). In this case, the firm’s first-order condition, in logs (indicated by lowercase), is given by:

$$e_{jt} = \frac{1}{1 - \phi} \left( \ln \frac{\phi}{W_t} + a_{jt} \right) \quad (\text{A3})$$

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<sup>1</sup> All of the code used to produce the results in the paper can be found at [openicpsr-120432](https://openicpsr-120432).

<sup>2</sup> We use the term “firm” for expositional purposes; in model exercises we do not distinguish between firms and establishments. Our empirical exercises using TFP measures and manufacturing data rely on establishments, while our economywide exercises using RLP rely on firms.

where  $W_t$  is the industry wage. Taking time differences (indicated by  $\Delta$ ) and sweeping out year and industry effects yields the firm-level growth rate (measured as log first differences for convenience):

$$\Delta e_{jt} = \frac{1}{1 - \phi} \Delta a_{jt} \quad (\text{A4})$$

Equation (A4) provides an employment growth function that is different from its expression in (A1); in particular, (A4) expresses employment growth as a function of the *change* in  $a_{jt}$ , which is intuitive in this frictionless environment (note also the importance of revenue function curvature parameter  $\phi$ ). However, (A4) can be transformed to express employment growth as a function of the productivity *level* instead. To see this, we start with (A3), consider it for  $t - 1$ , and invert it to express productivity in terms of employment:

$$a_{jt-1} = (1 - \phi)e_{jt-1} - \ln \frac{\phi}{W_{t-1}} \quad (\text{A5})$$

Substituting (A5) into (A4) (and, again, sweeping out industry and year effects) yields:

$$\Delta e_{jt} = \frac{1}{1 - \phi} a_{jt} - e_{jt-1}, \quad (\text{A6})$$

That is, employment growth can be expressed as a function of the *level* of  $a_{jt}$ , as well as the level of  $e_{jt-1}$ , as in (A1) and (A2). This is useful for two reasons. First, as noted in the text, it is convenient to specify the growth function in terms of productivity levels for empirical purposes, since productivity data in manufacturing are constructed to be representative in the cross section but not necessarily longitudinally. Second, in models with labor adjustment costs (such as the one we will describe below), the productivity level is the relevant state variable arising from the firm value function.

We now turn to two illustrative special cases of the general model framework that can motivate (A1) and (A2): a model with labor adjustment costs, and a model with static distortionary wedges that are correlated with fundamentals. We explore these models to demonstrate how (A1) arises from firm optimization problems and how it is affected by model parameters and frictions or distortions on employment demand decisions.

#### *B. Model with labor adjustment costs*

Consider the following model of firm-level adjustment costs. A firm maximizes the present discounted value of profits. The firm's value function and its components are specified as follows:

$$V(E_{jt-1}, A_{jt}) = \max\{A_{jt}E_{jt}^\phi - W_t E_{jt} - C(H_{jt}, E_{jt-1}) + \beta \mathbb{E}_A(E_{jt}, A_{jt+1})\} \quad (\text{A7})$$

with

$$C(H_{jt}, E_{jt-1}) = \begin{cases} \frac{\gamma}{2} \left( \frac{H_{jt}}{E_{jt-1}} \right)^2 + F_+ \max(H_{jt}, 0) + F_- \max(-H_{jt}, 0) & \text{if } H_{jt} \neq 0 \\ 0 & \text{otherwise} \end{cases}$$

where  $\phi < 1$  due to product differentiation such that  $A_{jt}E_{jt}^\phi$  is the revenue function for firm  $j$ ,  $E_{jt}$  is employment for time  $t$ ,  $H_{jt}$  is net hires made at the beginning of time  $t$  such that  $H_{jt} = E_{jt} - E_{jt-1}$  (this can be positive or negative),  $W_t$  is the wage, and  $A_{jt}$  is a composite shock reflecting both technical efficiency and demand shocks. We interpret the revenue function curvature as reflecting product differentiation rather than decreasing returns to help draw out the potential relationship between revenue productivity and technical efficiency when prices are endogenous. That is, let firm-level price be given by  $P_{jt} = D_{jt}Q_{jt}^{\phi-1}$ , where  $Q_{jt} = \tilde{A}_{jt}E_{jt}$  is firm-level output subject to a constant returns technology, with  $A_{jt} = D_{jt}\tilde{A}_{jt}^\phi$ . That is,  $A_{jt}$  is what we refer to as ‘‘TFP’’ in the main text and reflects both technical efficiency and demand shocks, both in the conceptual framework and empirical analysis. Since labor is the only production factor, TFPR and revenue labor productivity (RLP) are both given by  $P_{jt}\tilde{A}_{jt}$ . Note that in the alternative price-taking version of the model (where  $\phi = 1$ ), TFP, TFPR, and RLP are equivalent. We focus on the  $\phi < 1$  case in our calibration. We also abstract from demand shocks for clarity of exposition (i.e.,  $D_{jt} = 1 \forall j, t$ ) in the remaining discussion. Our TFP shocks should be interpreted as reflecting the type of composite shocks we consider empirically.

This simple adjustment cost model is similar to Cooper, Haltiwanger, and Willis (2007, 2015), Elsby and Michaels (2013), and Bloom et al. (2018) and, in principle, accommodates both convex and non-convex adjustment costs. In particular, given the cost function  $C(H_{jt})$ , which depends upon  $E_{jt-1}$ , the policy rule for hiring depends on the initial *state* faced by the firm, which is summarized as  $(E_{jt-1}, A_{jt})$ .

We view the model as primarily illustrative but seek a reasonable baseline calibration that matches key features of the data and the parameters of the existing literature. Appropriate caution is needed since we do not model entry or exit, and we do not have any lifecycle learning dynamics or frictions that make young firms different from more mature firms. We regard the

calibration as providing guidance about the qualitative predictions for the key data moments we study but within a reasonable range of the parameter space.

Our main calibration exercise, described in detail below, implements “general equilibrium” in the sense that we fix the labor supply then find the wage that clears the labor market. Given a rigid labor supply, this may be thought of as an extreme scenario. However, in unreported exercises we consider the opposite extreme in which labor supply is perfectly elastic and the wage is fixed (i.e., partial equilibrium). A limitation of the partial equilibrium exercise is that when the wage is fixed, adjustment frictions can have large effects on average firm size and therefore productivity via channels that are unrelated to reallocation. However, our key results on how adjustment costs affect reallocation rates, firm-level productivity responsiveness, and the effect of changing responsiveness on aggregate productivity growth do not substantively depend on general versus partial equilibrium.

Our method for solving the model is as follows. We create a state space for employment, with 2,400 points (distributed more densely at lower values), and for TFP realizations, with 115 points. We specify firm-level TFP to follow an AR(1) process,  $\ln A_{jt} = \rho_a \ln A_{jt-1} + \eta_{jt}$ , and in practice we use a Tauchen (1986) method for generating TFP draws. Table A1 reports our calibration choices, some of which are standard in the literature and others of which are designed to target specific data moments. We describe two alternative adjustment cost specifications: kinked adjustment costs (as described in the main text) and convex adjustment costs. We start with the kinked adjustment cost case. Empirically determined calibration choices are intended to produce a model economy that resembles the U.S. manufacturing sector in the 1980s, the initial timing of our empirical exercises, but the qualitative model results in which we are interested are not sensitive to these specific calibration choices.

We obtain policy functions using value function iteration then simulate 2,000 firms for 1,000 periods, jumping off from the stationary distribution of productivity but discarding the first 100 periods. Given a fixed (inelastic) labor supply, we check market clearing then adjust the wage using simple bisection until the labor market clears. We estimate responsiveness regressions and construct other statistics described in the text by using the simulated data generated by the model when in equilibrium.

We perform several exercises on the model-simulated data with a focus on three key outcomes: aggregate job reallocation, the dispersion of revenue productivity (where in the model,

revenue productivity is given by  $A_{jt}E_{jt}^{\phi-1}$ ), and the responsiveness of growth to productivity as measured with the regression in equation (2) of the main text. In other words, we measure the standard deviation of labor productivity in the model economy, and we estimate the regression from (A2), that is,

$$g_{jt} = \beta_0 + \beta_1 a_{jt} + \beta_2 e_{jt-1} + \varepsilon_{jt}, \quad (\text{A8})$$

where, as in the main text,  $g_{jt}$  is DHS employment growth from year  $t - 1$  to year  $t$ ,  $a_{jt}$  is productivity, and  $e_{jt-1}$  is (initial) employment. This is the same as equation (A2) and follows a timing convention that is analogous to our empirical work (though we confirm below that this timing convention is unimportant for the model’s qualitative results). “Responsiveness” is measured by  $\beta_1$ .

We study labor productivity dispersion and responsiveness under two model experiments starting from the model’s baseline calibration. In our first experiment, we study the effects of declining responsiveness, in this case resulting from a rise in adjustment costs. In particular, starting with the baseline calibration (where upward adjustment has a cost parameter of  $F_+ = 1.03$ ) we raise the cost of downward adjustments ( $F_-$ ). Figure 2 in the main text shows the result of this experiment. Rising adjustment costs generate declining reallocation (Figure 2a) due to lower responsiveness (2c), with the additional result of wider labor productivity dispersion, each of which we observe in our empirical exercises. This experiment suggests that declining responsiveness, as generated by rising labor adjustment costs, can cause declining reallocation, with the additional symptom of rising labor productivity dispersion.

In our second experiment, we reduce the parameter governing TFP dispersion, starting from its baseline calibrated value of  $\sigma_a = 0.46$ . This is also reported in Figure 2 in the main text. As TFP dispersion falls, aggregate job reallocation declines (Figure 2b), labor productivity dispersion decreases, and responsiveness becomes weaker (Figure 2d; we discuss this more below). This summarizes the “shocks” hypothesis: the declining pace of job reallocation we observe empirically could be explained by declining dispersion of TFP realizations if we were to also observe declining labor productivity dispersion. As shown in the main text, however, we actually observe rising labor productivity dispersion in our empirical work.

We must make one side note here: As noted above and shown in Figure 2c, in the model with non-convex adjustment costs, when shock dispersion declines, so too does responsiveness. At first glance, this dispersion dependence of responsiveness in the non-convex costs model may

complicate the shocks vs. responsiveness hypothesis. However, three points are important to note. First, this is unique to the model with non-convex costs; as we will discuss below (and show in Figures A1 and A2), responsiveness is unaffected by changes in dispersion when adjustment costs are convex, or in the correlated wedges model without adjustment costs. Second, we can easily conclude that the declining responsiveness we observe in the data is not driven by declining shock dispersion because we also empirically find rising shock dispersion (apparent in our TFPS and TFPP productivity measures) and rising revenue productivity dispersion (apparent in our TFPR and revenue labor productivity measures). Third, as we show in the main text, using industry variation we find no monotonic relationship between changes in TFP dispersion and changes in responsiveness.

The model results are robust to a wide range of conditions. Figure A3a shows that responsiveness regressions using lagged (rather than current) TFP or current RLP make the same qualitative predictions as regressions using lag TFP, as do regressions using current TFP *innovations* or *differences* (in the main text, we also find that our empirical results are robust to using innovations or differences).

Figure A3b reports responsiveness coefficients from instrumental variables regressions performed on model-simulated data; these correspond with those we estimated on empirical data (described in the main text, Appendix III.B, and Table A2) and are motivated by concerns about division bias and measurement error in employment. Figure A3c addresses the measurement error issue more specifically by considering scenarios in which the econometrician observes firm employment, firm labor productivity, or both with error.<sup>3</sup> Error in employment measurement is introduced with a multiplicative disturbance term drawn from an independent normal distribution with mean 1 and standard deviation 0.033 (such that employment disturbances of 10 percent map to three standard deviations from the mean);<sup>4</sup> error in labor productivity measurement is generated by applying the employment disturbance term to the denominator in revenue per worker. As shown in Figure A3c, this source of measurement error does not dramatically affect responsiveness coefficients, such that the decline in responsiveness we observe empirically is unlikely to be caused by rising measurement error over time. That said, the best approach to

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<sup>3</sup> Recall that in our manufacturing regressions, the employment variable used to measure productivity, which comes from the ASM/CM, is independent of the employment variable used to measure employment levels and growth, which comes from the LBD.

<sup>4</sup> This choice is arbitrary and does not have qualitative implications.

concerns about measurement error is our empirical investigation using cross-industry variation, covered in the main text and Table 8.

Figure A4a reports the effects of rising adjustment costs on aggregate productivity in the model with non-convex adjustment costs. The black solid line shows true (model) aggregate productivity. The dashed orange line replicates the productivity index exercise described in section IV.B of the main text; in that exercise, we empirically estimate the effects of declining responsiveness on aggregate productivity by constructing an aggregate productivity index that depends on estimated responsiveness coefficients (see that discussion for more detail).

The productivity index used in section IV.B is given by  $\sum_j \theta_{jt} a_{jt}$ , where  $\theta_{jt}$  is the employment weight of firm  $j$  and  $a_{jt}$  is TFP; we can construct this index and related counterfactuals using model-simulated data to study the index's relationship with true productivity. For every adjustment cost scenario, we use simulated data and corresponding regression coefficients to construct  $\sum_j \hat{\theta}_{jt}^{HC} a_{jt}$ , the aggregate productivity index as predicted by the responsiveness regressions under that adjustment cost scenario (where "HC" stands for "high cost"). We then construct a counterfactual index using the same simulated data but applying the responsiveness coefficient from the low-cost baseline scenario,  $\sum_j \hat{\theta}_{jt}^B a_{jt}$  (where "B" stands for baseline, referring to the use of the responsiveness coefficient from the low-cost baseline scenario). Then  $\sum_j \hat{\theta}_{jt}^{HC} a_{jt} - \sum_j \hat{\theta}_{jt}^B a_{jt}$  is the effect of changing responsiveness on the aggregate productivity index, in the model-simulated data. The dashed orange line in Figure A4a shows this counterfactual productivity index, which tracks true aggregate productivity reasonably well, lending support to our empirical approach for estimating the effects of changing responsiveness on aggregate productivity.

Our shocks vs. responsiveness approach is also useful if changing responsiveness is generated by convex labor adjustment instead of non-convex. We construct an alternative baseline calibration of the model in which non-convex costs are set to zero ( $F_- = F_+ = 0$ ), but  $\gamma=1.75$  to again replicate a job reallocation rate of 0.18, leaving all other parameters unchanged relative to Table A1. (Recall from the model description that  $\gamma$  governs quadratic adjustment costs on employment). From this alternative convex cost baseline, we conduct both of our model experiments: (1) raise adjustment cost  $\gamma$  above its baseline value, and (2) reduce TFP dispersion  $\sigma_a$ . These results are in Figure A1. The qualitative results of the experiments for job

reallocation, responsiveness, and revenue productivity dispersion are the same as those found in our non-convex cost experiments except that, as mentioned above, responsiveness is unaffected by changes in shock dispersion (providing an even cleaner shocks vs. responsiveness dichotomy). The productivity results for the convex cost case are reported in Figure A4b.

Finally, we note that declining responsiveness can also be derived from an increase in the curvature of the revenue function (generated by reducing  $\phi$ ). This is shown in Figure A3d; notably, while increased curvature reduces responsiveness in each of our example model frameworks, its implications for revenue productivity dispersion (not shown) are model dependent.

### C. *Alternative framework: Wedges*

The shocks vs. responsiveness insight is more general than the specific adjustment costs models described above. As an example, here we show how a broader interpretation can be adopted, following the seminal work of Hsieh and Klenow (2009).

Hsieh and Klenow (2009) show how measured revenue productivity dispersion can exist in equilibrium if there are static distortions or “wedges” affecting firms’ first-order conditions. This framework can be viewed as a reduced form way of capturing not only adjustment frictions (under certain specifications of the wedge process) but also a wide variety of other factors that distort first-order conditions.

Consider a simple one-factor (employment) model in the spirit of Hsieh and Klenow (2009). Firms maximize period  $t$  profits given by:

$$S_{jt}A_{jt}E_{jt}^{\phi} - W_tE_{jt} \quad (\text{A9})$$

where  $A_{jt}E_{jt}^{\phi}$  is revenue and  $S_{jt}$  is a firm-specific wedge, which can be thought of as a tax when  $S_{jt} < 1$  or as a subsidy when  $S_{jt} > 1$ . Suppose the wedge  $S_{jt}$  follows the following process:

$$s_{jt} = -\kappa a_{jt} + v_{jt}, \quad (\text{A10})$$

where lowercase indicates logs. Consistent with much of the recent literature, we assume  $\kappa \in (0,1)$ , and  $v_{jt}$  is independent of  $a_{jt}$  with  $E(v_{jt}) = 0$ .<sup>5</sup> Equation (A10) states that firms with more favorable fundamentals (e.g., higher TFP) face more substantial wedges (meaning, lower

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<sup>5</sup> By “consistent with the literature,” we mean a common finding in the literature is that indirect measures of wedges (i.e., revenue productivity measures like TFPR) are positively correlated with measures of fundamentals (technical efficiency and demand shocks) and have lower variance than fundamentals. See Foster, Haltiwanger, and Syverson (2008) and Blackwood et al. (forthcoming).

$S_{jt}$ ), but the variance of (log) wedges is lower than the variance of fundamentals. This relationship between  $S_{jt}$  and  $A_{jt}$  is critical for producing empirically plausible aggregate reallocation rates (under reasonable parameterizations of  $\phi$ ) in the absence of explicit adjustment frictions.

Given (A9) and (A10), the first-order condition, in logs (indicated by lowercase), is given by:

$$e_{jt} = \frac{1}{1-\phi} \left( \ln \left( \frac{\phi}{w_t} \right) + (1-\kappa)a_{jt} + v_{jt} \right). \quad (\text{A11})$$

Taking time differences (indicated by  $\Delta$ ), sweeping out year and industry effects, and incorporating the transformation described in the first section of this appendix, we obtain an employment growth function (expressed in log differences):

$$\Delta e_{jt} = \frac{1}{1-\phi} \left( (1-\kappa)a_{jt} - (1-\phi)e_{jt-1} + v_{jt} \right). \quad (\text{A12})$$

Employment growth can be expressed as a function of the productivity level and lagged employment, along with the shock to the wedge and the model parameters. Equation (A12) shows that the relationship between employment growth and productivity depends not only on  $\phi$  but also on  $\kappa$ , which determines the covariance between firm productivity and firm distortions. A higher value of  $\kappa$  results in weaker responsiveness of growth to productivity because stronger  $\kappa$  means that wedge shocks partially offset productivity shocks. In the text, we refer to a higher  $\kappa$  as reflecting a more positive correlation between fundamentals and distortions. By this we mean that the implicit tax on firms is increasing in fundamentals. In this case the implicit tax is larger the less positive is  $s_{jt}$ . Note also that aggregate job reallocation, which in this context can be thought of as the dispersion of employment growth rates, is decreasing in  $\kappa$ .

This framework also has implications for revenue productivity dispersion. Log revenue per worker is given by  $\ln \frac{w_t}{\phi} + \kappa a_{jt} - v_{jt}$ , such that the dispersion of revenue labor productivity is *increasing* in  $\kappa$ .

This model, albeit highly simplified, thus yields rich empirical predictions, which we report in a manner analogous to our simulations from the model with labor adjustment costs. That is, we calibrate the “wedges” model, using the wedge correlation parameter  $\kappa$  to target the empirical reallocation rate of the 1980s, then we conduct experiments varying  $\kappa$  and  $\sigma_A$  (the dispersion of TFP). These exercises are shown in Figure A2 in a manner comparable to Figures

2 and A1. Figures A2a and A2c report the results of raising  $\kappa$  from its baseline value; as discussed above, responsiveness and job reallocation fall while revenue labor productivity dispersion rises. Declining responsiveness through this mechanism, as in the other models, yields a decline in aggregate productivity, as shown in Figure A4c.

The wedge model also yields similar implications for changes in the variance of shocks, shown in Figure A2b. A decline in the variance of  $a_{jt}$  yields declining reallocation and revenue productivity dispersion but, as in the model with convex adjustment costs, does not affect responsiveness (thus, responsiveness depends on TFP dispersion only in the model with non-convex adjustment costs).

Finally, as in the models with adjustment costs, in the wedge model a decline in responsiveness can be generated through a decline in revenue function curvature, as shown in Figure A3d.

## **Appendix II: Data**

### *A. Longitudinal Business Database*

For longitudinal information we rely on the Longitudinal Business Database (LBD), which covers the universe of private nonfarm employer business establishments in the U.S. The LBD records establishment employment, payroll, detailed industry, and location annually (with employment corresponding to March 12). Establishments are linked over time by high-quality longitudinal identifiers, and firm identifiers link establishments of multi-establishment firms. See Jarmin and Miranda (2002) for a description of the LBD, which is constructed from the Census Bureau's Business Register. The LBD's high-quality longitudinal linkages make it ideal for studying growth and survival outcomes of businesses.

In our regression specifications we include several establishment characteristic controls derived from the LBD. Key among them is firm age. We follow the large LBD-based literature in defining firm age as follows. Upon the first appearance of a firm identifier in the LBD, we assign firm age as the age of the firm's oldest establishment, where an establishment has age 0 during the year in which it first reports positive payroll. Thereafter, the firm ages naturally (i.e., we add one year to the firm's age for each calendar year after the firm identifier's first observation). This allows us to abstract from spurious changes in firm identifiers. We also use firm identifiers to measure firm size, which is the sum of employment across all the firm's establishments. In our regressions we control for firm size based on four cutoffs: fewer than 250 employees, 250-499 employees, 500-999 employees, and 1,000 or more employees (these cutoffs follow Foster, Grim, and Haltiwanger (2016), hereafter FGH).

### *B. Revenue-enhanced LBD (RE-LBD)*

While the LBD does not include revenue data, revenue information is available in the Business Register at the employer identification number (EIN) level starting in the mid-1990s. Importantly, EINs are not a straightforward firm or establishment identifier in that multiple establishments can have the same EIN, and some firms can have multiple EINs (e.g., splitting the firm by geography or separating tax functions from payroll functions). In the case of multi-establishment firms, in general revenue data are not broken out by establishment. Haltiwanger et al. (2017) deal with these various challenges and create firm-level revenue data by aggregating

across EINs of the same firm.<sup>6</sup> They then match these revenue figures to the LBD at the firm level, finding nominal revenue figures for about 80 percent of LBD firms. The resulting revenue dataset is roughly representative of the overall LBD in terms of observables like firm age, firm size, sector, multi- or single-establishment status, and patterns of firm growth. Nevertheless, Haltiwanger et al. (2017) construct propensity scores for the entire LBD using logistic regressions with dependent variable equal to 1 for firms with revenue data and 0 otherwise. These regressions are run separately for birth, deaths, and continuers, and they rely on observables including firm size, firm age, employment growth rate, industry, and multi-establishment status. We use the resulting propensity scores (in inverse) as sampling weights in all regressions. We deflate revenue with the GDP deflator, but this is unimportant as all empirical exercises will implicitly control for industry-level prices as we deviate firm productivity from industry-year means. More generally, we follow Haltiwanger et al. (2017) closely in our measurement approach using the RE-LBD.

### *C. Manufacturing data*

We supplement the LBD with manufacturing data from the Census of Manufacturers (CM) and the Annual Survey of Manufacturers (ASM), a dataset we obtain from FGH and update through 2013. The CM surveys almost the universe of manufacturing establishments every five years (those ending in “2” and “7”); we use CM data from 1982 through 2012.<sup>7</sup> The ASM, conducted in non-CM years, surveys roughly 50,000-70,000 establishments; we use ASM data from 1981 through 2013. The ASM is a series of five-year panels (starting in years ending in “4” and “9”) with probability of panel selection being a function of industry and size.

We combine the CM and ASM into an annual manufacturing establishment dataset covering 1981-2013, and we link the combined ASM-CM with the LBD by establishment and year using internal Census Bureau establishment identifiers that are consistent across these datasets. We create a dummy variable equal to 1 for those establishments that appear in both the ASM-CM and the LBD and 0 for those establishments that appear only in the LBD. We then create propensity scores using a logistic regression to predict ASM-CM presence based on the following variables: whether the establishment is part of a multi-establishment firm, size

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<sup>6</sup> This is a complicated process involving careful attention to details including industry and legal form of organization, which can affect the way in which revenue data are reported and the way EINs map to firms.

<sup>7</sup> Very small establishments (those with fewer than five employees) are not surveyed by the CM; the Census Bureau fills in data for these with administrative records. We do not include these cases.

(employment), payroll, detailed industry, and firm age. We estimate these propensity scores separately for each year; we then use them (in inverse) as sampling weights in all regressions.

As discussed in the main text, we use the LBD to measure employment growth and survival for each plant-year observation for which we have the TFP measures. This implies we are using the LBD through 2014 for this purpose.

#### D. Output and production factors

We require measures of revenue and production factors to construct TFPS, TFPP, and TFPR. We calculate real establishment-level revenue (or, under TFPR assumptions, output) as  $R_{jt} = (TVS_{jt} + DF_{jt} + DW_{jt})/PISHIP_t$ , where  $TVS_{jt}$  is total value of shipments,  $DF_{jt}$  is the change in (the value of) finished goods inventories,  $DW_{jt}$  is the change in (the value of) work-in-progress inventories, and  $PISHIP_t$  is the *industry-level* shipments deflator, which varies by detailed industry (4-digit SIC prior to 1997 and 6-digit NAICS thereafter) and is taken from the NBER-CES Manufacturing Productivity Database. If the resulting  $R_{jt}$  is not greater than zero, then we simply set  $R_{jt} = TVS_{jt}/PISHIP_t$ .

For the purposes of TFP estimation, we construct labor from the ASM in terms of total hours ( $TH_{jt}$ ) as follows:

$$TH_{jt} = \begin{cases} PH_{jt} \frac{SW_{jt}}{WW_{jt}} & \text{if } SW_{jt} > 0 \text{ and } WW_{jt} > 0 \\ PH_{jt} & \text{otherwise} \end{cases} \quad (\text{A13})$$

where  $PH_{jt}$  is production worker hours,  $SW_{jt}$  is total payroll, and  $WW_{jt}$  is the payroll of production workers.

We measure capital separately for structures and equipment using the perpetual inventory method:  $K_{jt+1} = (1 - \delta_{t+1})K_{jt} + I_{jt+1}$  where  $K$  is the capital stock,  $\delta$  is a year- (and industry-) specific depreciation rate, and  $I$  is investment. At the earliest year possible for a given establishment, we initialize the capital stock by multiplying the establishment's reported book value by a ratio of real capital to book value of capital derived from BEA data (where the ratio varies by 2-digit SIC or 3-digit NAICS). Thereafter, we observe annual capital expenditures and update the capital stock accordingly, where we deflate capital expenditures using BLS deflators.<sup>8</sup>

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<sup>8</sup> See FGH for more detail. In a small number of cases (less than 0.5 percent) we cannot initialize the capital stock as described; in such cases we follow Bloom et al. (2013) using I/K ratios.

We calculate materials as  $M_{jt} = (CP_{jt} + CR_{jt} + CW_{jt})/PIMAT_t$ , where  $CP$  is the cost of materials and parts,  $CR$  is the cost of resales,  $CW$  is the cost of work done for the establishment (by others) on the establishment's materials, and  $PIMAT$  is the industry materials deflator. We calculate energy costs as  $N_{jt} = (EE_{jt} + CF_{jt})/PIEN_t$ , where  $EE$  is the cost of purchased electricity,  $CF$  is the cost of purchased fuels consumed for heat, power, or electricity generation, and  $PIEN$  is the industry energy deflator.

We use the production factor and output measures described above for each of our three TFP measures (TFPS, TFPP, and TFPR).

*E. Cost and revenue shares: TFPS and TFPR*

TFPS and TFPR productivity estimates require industry-level factor expenditures as shares of revenue (for TFPS) or cost (for TFPR) to construct factor elasticity estimates. We obtain these shares at the detailed industry level (4-digit SIC prior to 1997, 6-digit NAICS thereafter) from the NBER-CES Manufacturing Productivity Database, which reports industry-level figures for expenditures on equipment, structures, materials, energy, and labor. We average these cost shares across all of 1981-2013 to obtain time-invariant elasticities, though our results are robust to instead using time-varying elasticities as in FGH.

*F. Proxy method: TFPP*

Our TFPP productivity concept requires us to estimate factor elasticities using proxy methods. Given the challenge of identifying exogenous shocks to fundamentals, a long literature (e.g., Olley and Pakes (1996), Levinsohn and Petrin (2003)) proposes using a variable production factor as a “proxy” for identification. Blackwood et al. (forthcoming) compare multiple proxy-based TFP concepts with other concepts from the literature. Some literature achieves this using a two-step procedure (see Akerberg, Caves, and Frazer (2015)), but we follow Wooldridge (2009) in implementing a single-step GMM approach using lagged values of capital and variable inputs as instruments. We refer the reader to the just-mentioned research for more detail on the general approach to proxy estimation of production functions. For our purposes, we estimate factor elasticities separately by 2- and 3-digit industries using energy as the proxy variable.

### Appendix III: Additional empirical results

#### A. Reallocation has declined within firm age bins

As noted in the text, the aggregate decline in job reallocation is not simply a composition effect due to declining young firm activity. Rather, we also observe declining reallocation within firm age bins. To see this, we first create seven firm age groups (ages 0, 1, 2, 3, 4, 5 and 6+). We then study the change in aggregate (weighted average) job reallocation in year  $t$  relative to a base year  $t_0$  with the following shift-share decomposition:

$$R_t - R_{t_0} = \sum_a \omega_{at_0}(R_{at} - R_{at_0}) + \sum_a R_{at_0}(\omega_{at} - \omega_{at_0}) + \sum_a (R_{at} - R_{at_0})(\omega_{at} - \omega_{at_0})$$

where  $R_t$  is the aggregate (or, as we will specify it below, sector-level) job reallocation rate,  $a$  indexes age bins,  $\omega_{at}$  is the employment share of age group  $a$  in time  $t$ , and  $R_{at}$  is the reallocation rate for age group  $a$  in time  $t$ . The first term is a within-age-group component based on the change in flows among firms of that age. The second term is a between-group component capturing the change in the age composition. The third term is a cross term. We focus on the overall component and the within component; the residual coming from composition shifts and cross terms reflects the extent to which composition effects account for the aggregate change.

To abstract from business cycle issues, we construct this counterfactual between the business cycle peaks of 1987-1989, 1997-1999, 2004-2006, and 2011-2013. We study the long differences in reallocation rates between these three periods. Figure A5 illustrates the results, showing both the overall change in reallocation for a sector and the change in the within-age-group term, indicated by the “Holding age constant” bars. As is evident, the decline in reallocation within age groups explains the bulk of the overall decline. In other words, the changing age composition of U.S. firms resulting from changing patterns of firm entry does not explain the patterns of reallocation that motivate this paper.

#### B. Instrumental variables: Empirical results

A particular challenge for our empirical approach is that our workhorse regressions given by equations (7) and (9) in the main text feature initial employment ( $E_{jt}$ ) on the right-hand-side (as the state variable) and on the left-hand-side (in the DHS growth dependent variable). Additionally, in our economywide regressions using labor productivity, initial employment also

appears in the denominator of the productivity indicator (which is real revenue per worker).<sup>9</sup> In Appendix I, we explore this problem by running instrumental variables regressions on model-simulated data. Regressions in which an employment lag is used to instrument for initial employment (i.e., use  $E_{jt-1}$  as an instrument for  $E_{jt}$ ), and regressions in which we additionally instrument for productivity using a lag, find that responsiveness still declines as adjustment costs rise. This suggests that we can evaluate robustness of our main responsiveness results to the employment endogeneity issue using similar instrumental variables regressions in our empirical exercises.

For brevity, we focus on the time-trend regression specifications for studying changing responsiveness. Table A2 reports results of instrumental variables regressions. The first column reports establishment-based results for the manufacturing sector using our preferred productivity measure, TFPS, and instrumenting for initial employment. The second column reports economywide firm-based results instrumenting for initial employment, and the third column reports economywide firm-based results instrumenting for initial employment and for productivity. In each column, and for both young and mature firms, we observe declining responsiveness as indicated by the negative (and statistically significant) coefficient on the linear trend variables.

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<sup>9</sup> Initial employment is also used in TFP estimation in our manufacturing-only exercises; however, the employment variable used for TFP is independently constructed from our ASM-CM dataset (see Appendix II).

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**Table A1: Baseline model calibration**

	Description	Value	Calibration rationale
$\phi$	Inverse demand elasticity parameter	0.67	Standard in literature
$\beta$	Discount factor	0.96	Standard in literature
$\rho_a$	(Log) TFP AR(1) coefficient	0.80	Estimated TFPS AR(1), 1980s average
$\sigma_a$	Standard deviation of (log) TFP	0.46	Estimated TFPS standard deviation, 1980s average
$\sigma_\eta$	Standard deviation of TFP innovation	0.28	Implied by $\rho$ and $\sigma_a$
$F_+$	Upward kinked adjustment cost	1.03	Target job reallocation rate = 0.18 (1980s average)* $F_+ = 0$ in convex cost model.
$F_-$	Downward kinked adjustment cost	0.00	(Rely on upward cost for baseline calibration)
$\gamma$	Convex adjustment cost parameter	0.00	No convex cost in non-convex cost model. $\gamma = 1.75$ in convex cost model.
$\kappa$	Wedge/productivity correlation parameter	0.83	Wedge model only; target job reallocation rate 0.18* With $\sigma_v = 0.04$ .

Moment targets refer to U.S. manufacturing sector.

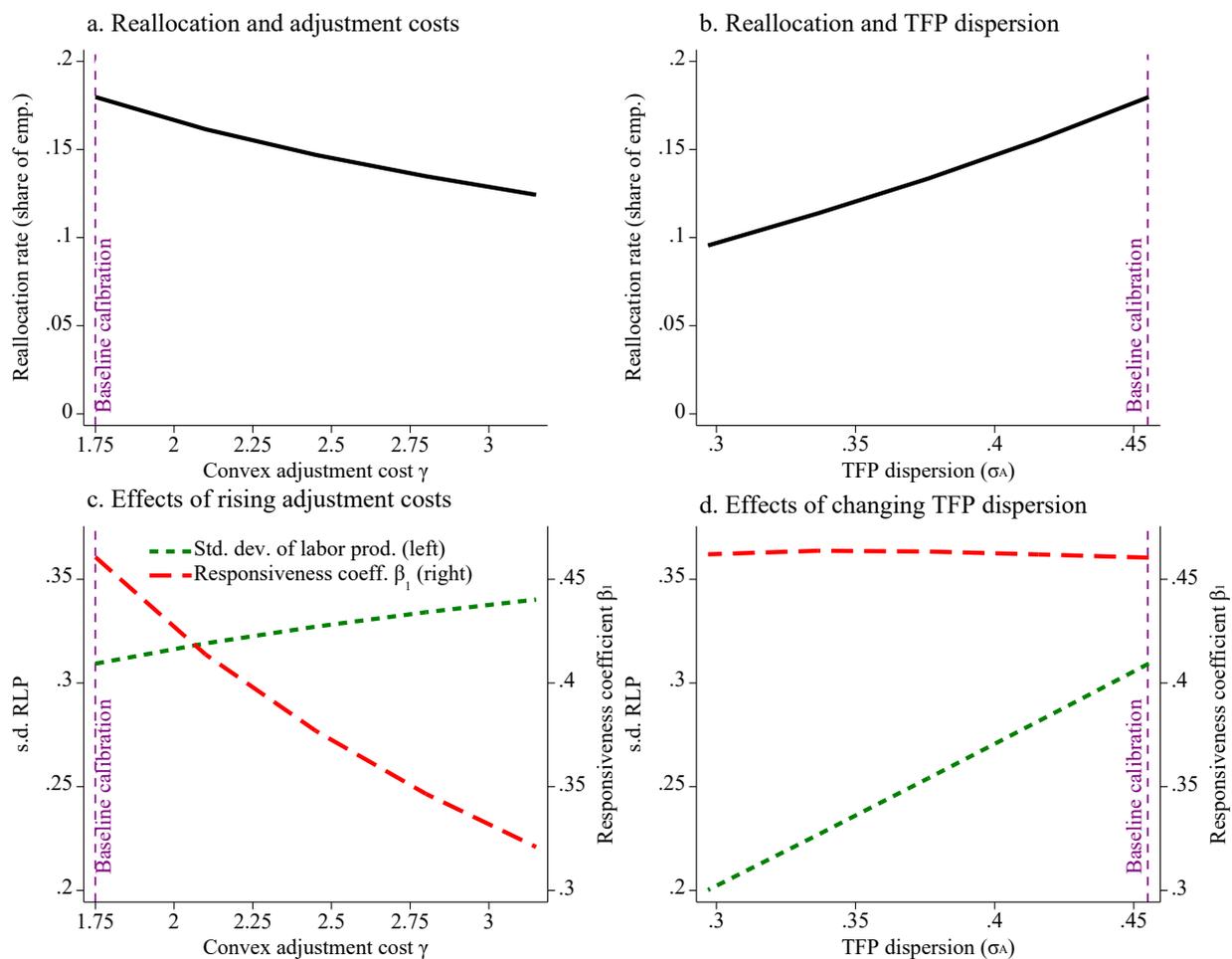
\*1980s average reallocation rate among continuing establishments (Business Dynamics Statistics).

**Table A2: Instrumental variables regressions, employment growth responsiveness**

	TFPS: IV for employment	RLP: IV for employment	RLP: IV for emp & RLP
Prod*Young: $\beta_1^y$	0.4358 (0.0177)	0.3170 (0.0013)	0.1499 (0.0016)
Prod*Young*trend: $\delta^y$	-0.0042 (0.0009)	-0.0033 (0.0001)	-0.0015 (0.0001)
Prod*Mature: $\beta_1^m$	0.3123 (0.0104)	0.2581 (0.0010)	0.1092 (0.0001)
Prod*Mature*trend: $\delta^m$	-0.0020 (0.0005)	-0.0032 (0.0001)	-0.0014 (0.0001)
Observations (thousands)	2,179	4,909	4,909

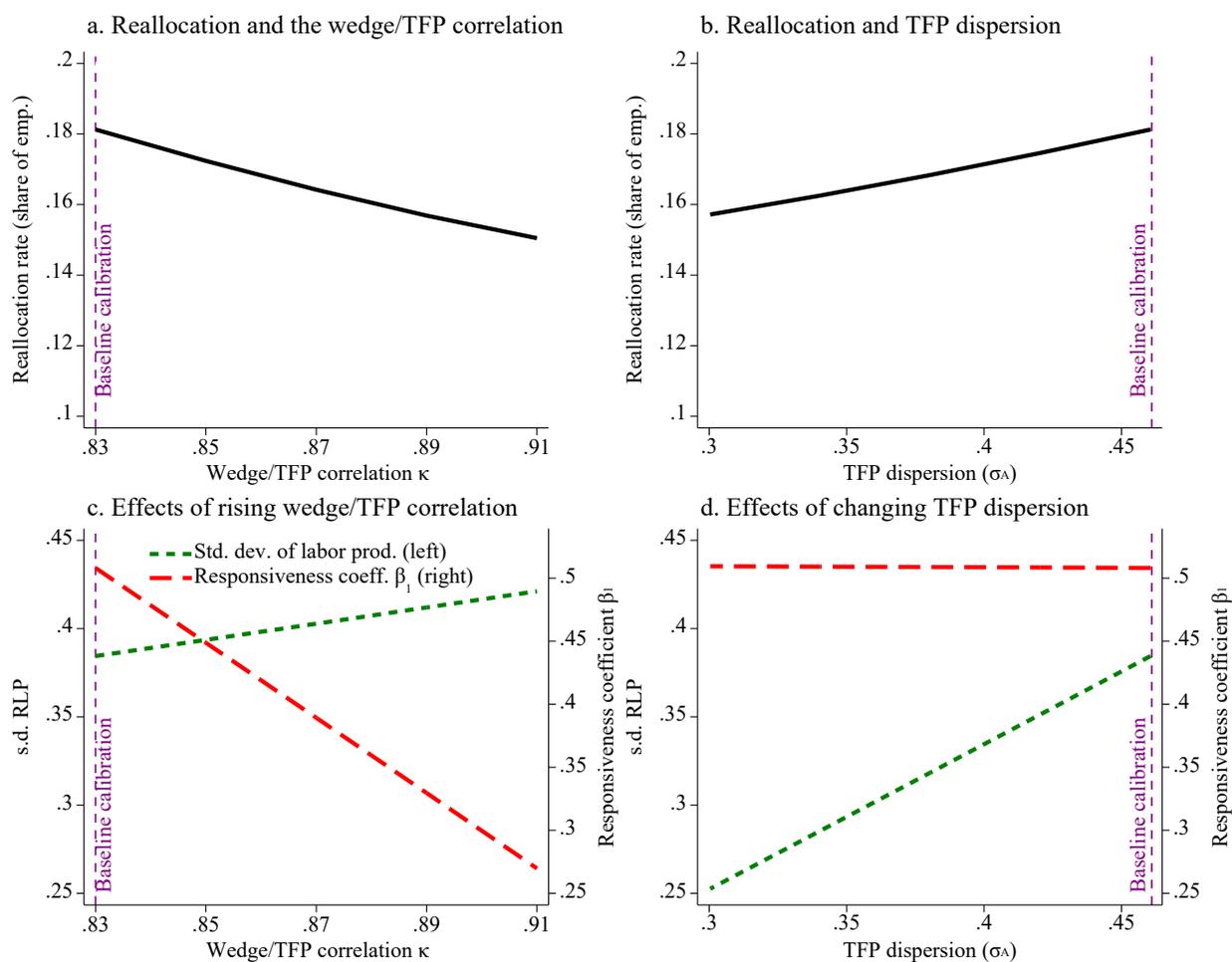
Note: All coefficients statistically significant with  $p < 0.01$ . All regressions include controls described in equation (7) and related text. RLP regressions use 10 percent random sample of RE-LBD.

**Figure A1: The shocks and responsiveness hypotheses, model results (convex cost)**



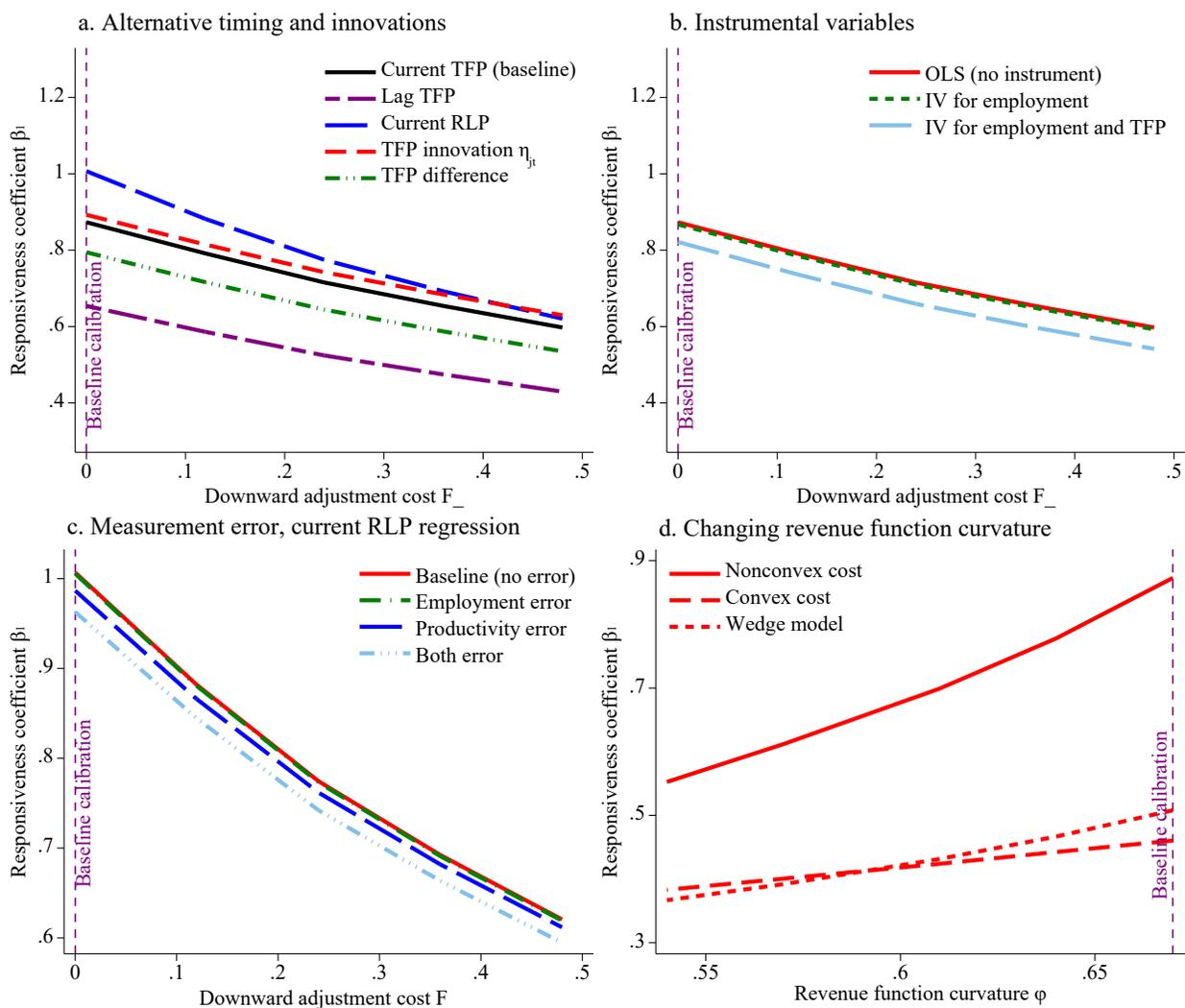
Note: Panels c and d share same legend. Results relative to model baseline calibration (vertical purple line) with downward adjustment cost  $\gamma=1.75$  and TFP dispersion  $\sigma_A=0.46$  (see Appendix I and Table A1 for model calibration details). "s.d. RLP" refers to the standard deviation of revenue labor productivity in model-simulated data.

**Figure A2: The shocks and responsiveness hypotheses, model results (wedge model)**

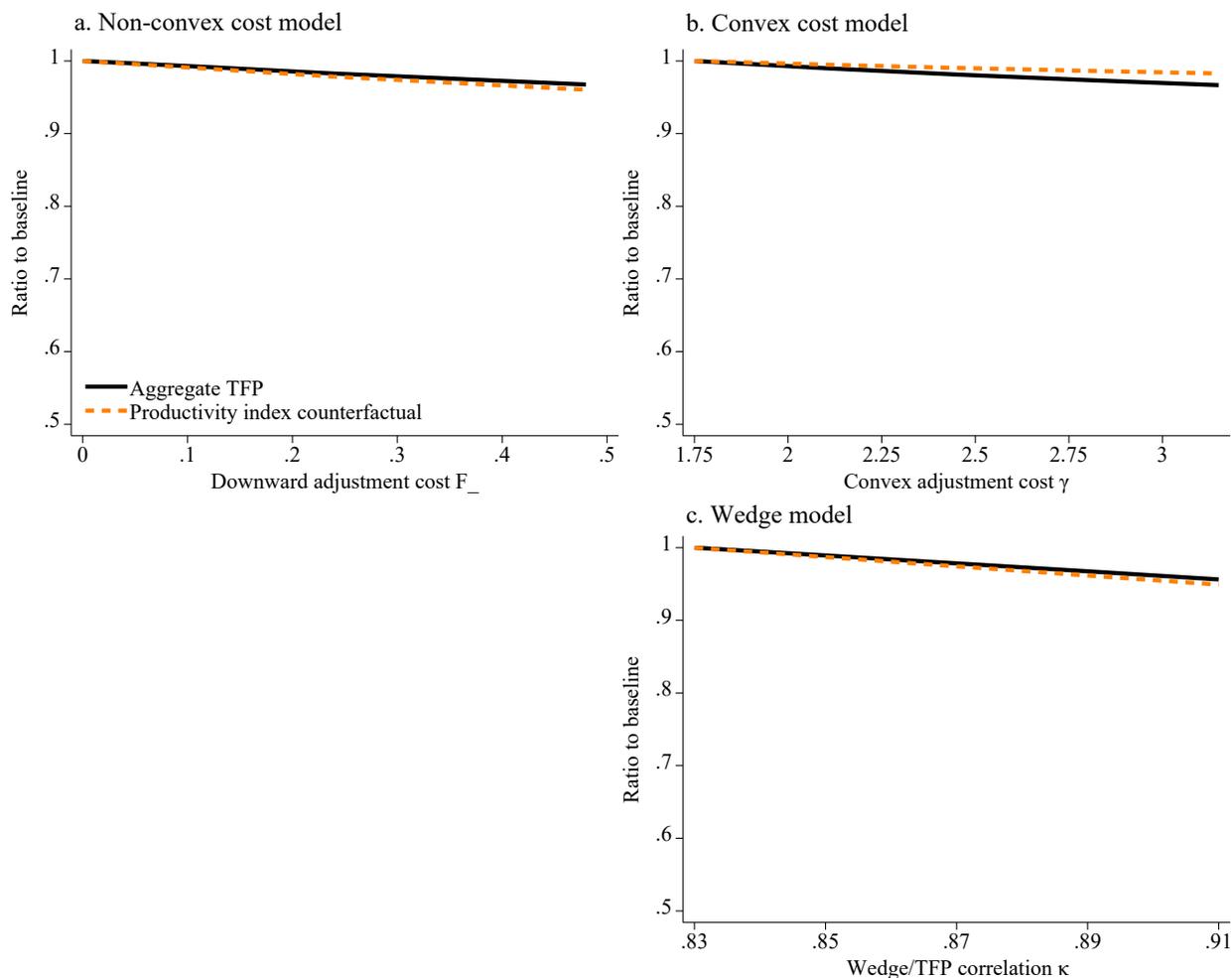


Note: Panels c and d share same legend. Results relative to model baseline calibration (vertical purple line) with TFP/wedge correlation parameter  $\kappa=0.83$  and TFP dispersion  $\sigma_A=0.46$  (see Appendix I and Table A1 for model calibration details). "s.d. RLP" refers to the standard deviation of revenue labor productivity in model-simulated data.

**Figure A3: Alternative responsiveness coefficient  $\beta$  specifications in model-simulated data**

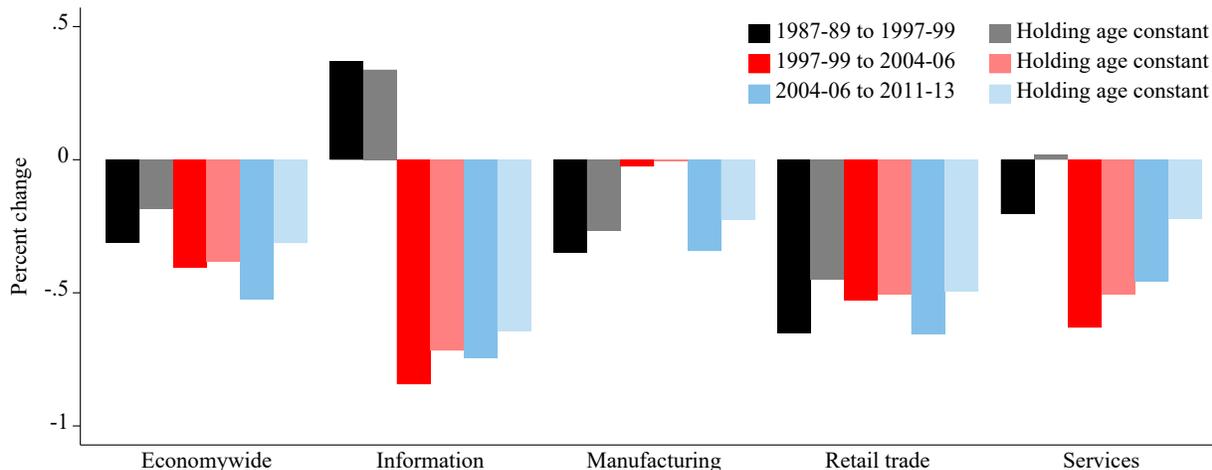


**Figure A4: Aggregate productivity and responsiveness**



Note: Model simulations. 'Estimated effects' reflect productivity counterfactuals in simulated data mimicking empirical exercises.

**Figure A5: Most variation in job reallocation is within firm age classes**



Note: Sectors are defined on a consistent NAICS basis. Source: LBD.