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Abstract

This paper analyzes how labor flows respond to permanent idiosyncratic shifts in firm-level production functions and demand curves using very detailed Swedish micro data. Shocks to firms' physical productivity have only modest effects on firm-level employment decisions. In contrast, the paper documents rapid and substantial employment adjustments through hires and separations in response to firm-level demand shocks. The choice of adjustment margin depends on the sign of the shock: firms adjust through increased hires if these shocks are positive and through increased separations if the shocks are negative.

JEL classifications: D22, J63, J23
Keywords: Technology, Demand, Job flows, Worker flows

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1 Introduction

About one in every five jobs is created or destroyed every year (Davis, Faberman, and Haltiwanger 2012). The bulk of this firm-level labor adjustment is truly idiosyncratic, as firms operating in the same sector and area shrink and grow side-by-side. Hence, jobs are rapidly created and destroyed, even in sectors with stable net employment. Following the seminal work of Davis, Haltiwanger, and Schuh (1996), the importance and magnitude of these job flows have been documented for a large number of countries. Similarly, for every job created or destroyed at the firm level, there is typically a larger number of worker hires and separations. Following in the tracks of Abowd, Corbel, and Kramarz (1999), the relationship between employment adjustments of different signs and magnitudes on one side, and worker flows on the other side, has been thoroughly investigated in several studies.[1] However, while the empirical regularities of job and worker flows have been abundantly documented, little is known about how job and worker flows respond to structural firm-level shocks.[2] In this paper, we use detailed Swedish register data to show that permanent shocks to firms' idiosyncratic product demand are a much more important source of job reallocation between firms than idiosyncratic technology shocks. We further show that the job reallocation induced by these permanent demand shocks generates excessive worker flows, because firms adjust to negative demand shocks through additional separations, instead of cutting down on hires.

We follow Foster, Haltiwanger, and Syverson (2008) and let technology and demand shocks summarize the set of idiosyncratic disturbances that may alter firms' demand for labor inputs. Technology shocks are defined as shifts in firms' ability to produce at a given level of inputs (i.e., shifts in the firms' physical production function), whereas demand shocks are defined as shifts in the firms' ability to sell at a given price (i.e., shifts in the firms' demand curve). To generate empirical measures of permanent technology and demand shocks, we derive a set of conditions arising from a stylized model of monopolistically competitive firms. To avoid imposing unnecessary

[1]See Davis, Faberman, and Haltiwanger (2012) for an overview. For evidence from Sweden, which is the empirical subject of this paper, see Andersson (2003).

[2]A small macro-oriented literature aims at identifying the employment responses to technology-driven changes in firm-level productivity: see, for example, Carlsson and Smedsaas (2007) and Marchetti and Nucci (2005). The macro literature also contains several related studies, such as Galí (1999) and Michelacci and Lopez-Salido (2007), the latter of which distinguishes between neutral technology shocks and investment-specific technology shocks and derives the consequences for job reallocation.

restrictions on firms' short-run adjustment behavior, we only assume that our derived conditions are valid in the long run. Therefore, inspired by Franco and Philippon (2007), we make use of structural vector autoregression (SVAR) methods, as originally outlined in Blanchard and Quah (1989), for estimation of the shocks. Using the SVAR allows us to filter out empirical measures of permanent idiosyncratic demand and technology shocks from the observed data without any assumptions about short-run dynamics. The focus on permanent shocks is motivated by the findings in Franco and Philippon (2007); Roys (2016); and Guiso, Schivardi, and Pistaferri (2005), suggesting that workers are insulated from transitory idiosyncratic shocks, a feature that is echoed in our empirical application.[3]

The most important imposed restriction is that demand shocks cannot affect the physical gross Solow residual in the long run. The long-run aspect of this restriction is crucial, since it implies that demand shocks, changes in factor utilization, or inventories are allowed to have a transitory impact on the physical Solow residual without affecting our measured technology shocks. We further derive sufficient restrictions to identify permanent demand shocks without imposing any restrictions on the nature of short-run shocks or dynamics but explicitly allowing for shocks to factor prices, which are likely to be important in a small open economy.

When taking the analysis to the data, we benefit from detailed Swedish register data covering the universe of workers and manufacturing firms with at least 10 workers during a 12-year period. A key aspect of our data is that they contain a firm-specific price index, which allows us to derive measures of firm-level real output volumes, which are needed to separate technology shocks from demand shocks. The data further allow us to mitigate standard macro-data concerns about the practical implementation of SVARs arising from imprecisely estimated parameter vectors and covariance matrices of the underlying set of reduced-form equations. In our case, we estimate these components using dynamic panel data methods, building on Arellano and Bond (1991), which allow us to use cross-sectional variation for identification of the crucial parameters. This provides substantial gains in power relative to standard time-series applications, including, for example, Franco and Philippon (2007), who

[3]Demand shocks have a nontrivial transitory component, which we abstract from in the main analysis and then study separately in Section 4.2. In contrast, the bulk of movements in the Solow residual are persistent enough to emerge as permanent shocks in our SVAR. This is consistent with Carlsson, Messina, and Nordström-Skans (2016), who, when estimating an AR(1) process for the level of technology using Swedish data similar to ours, find a persistence estimate as high as 0.88. Eslava et al. (2004) find an even higher persistence of 0.92 for Colombia.

estimate similar processes using time-series variation within firms.

The empirical analysis provides two important new insights. The first is that the main driving force behind employment adjustments is changes in labor demand that arise through permanent shocks from the product demand side, and not from cost-saving technology shocks. Firm-level technology shocks have a relatively limited effect on labor inputs, despite large effects on firm-level prices and output. In contrast, we find that permanent idiosyncratic variations in product demand have a major impact on firm-level labor adjustments. Our preferred estimates indicate that a permanent idiosyncratic demand shock of one standard deviation increases employment by 6 percent, whereas the corresponding number for technology shocks is 0.5 percent. These results are robust to a wide range of variations in measures and variations in the empirical approach.[4] We also find that most of the adjustment takes place within a year, which implies that the short- and long-run employment adjustments induced by permanent demand shocks are similar in magnitude. In contrast to the responses to these permanent demand shocks, we show evidence suggesting that firms' responses to transitory demand shocks are more muted.

Our second main result is that the responses of worker flows (hires and separations) are asymmetric, i.e., they depend on the sign of the underlying shock. Here we build on the seminal work of Abowd, Corbel, and Kramarz (1999) and Davis, Faberman, and Haltiwanger (2012), who provide descriptive decompositions of how worker flows are related to employment changes at the firm level. In contrast to these decomposition exercises, we analyze how hires and separations respond to job creation or destruction induced by permanent shifts in a firm's product demand schedule. We find that, while most of the response to permanent positive shocks is through increased hirings, by far most of the adjustment to permanent negative shocks is through increased separations, and not through reduced hirings. Firms continue to recruit workers at a rate that is not far off the average hiring rate, even while they are destroying jobs in response to a permanent fall in product demand. These results thus concur with the descriptive picture provided by Davis, Faberman, and Haltiwanger (2012) for the United States, but differ from Abowd, Corbel, and Kramarz (1999), who document

[4]The fact that employment responds so much more forcefully to permanent demand shocks relative to technology shocks is difficult to reconcile with a constant product-demand elasticity. However, we show that the magnitudes can be reconciled with models (consistent with our identifying assumptions) where the demand elasticity moves with the structural shocks. Furthermore, the implied sensitivity of the elasticity is modest in magnitude.

that employment reductions in French firms are primarily associated with reduced hiring rates.

Our analysis adds to a vibrant empirical literature, surveyed by Syverson (2011), who documents the distinct impacts of firm-level technology and demand shocks on productivity and other firm-level outcomes. Most notably, Foster, Haltiwanger, and Syverson (2008) show that firm closures are driven primarily by changes in idiosyncratic demand and only to a lesser extent by changes in idiosyncratic physical productivity. Eslava and Haltiwanger (2018) study the contribution of economic fundamentals, most notably technology and demand differences across firms, versus adjustment frictions to output and sales growth of Colombian establishments. Foster, Haltiwanger, and Syverson (2016) show that the growth of young firms in the United States is due to a shrinking product-demand gap relative to incumbents. Pozzi and Schivardi (2016), who use Italian data to analyze how technology and demand affect firm output, show that firm-level technology shocks have a surprisingly low impact on firm growth, and that demand shocks are at least as important. Studies analyzing employment adjustments in response to shocks also include Caballero, Engle, and Haltiwanger (1997) and Eslava et al. (2010). In addition, Carlsson, Messina, and Nordström-Skans (2016) show that firm-level technology shocks affect workers' wages, using Swedish data.

This paper is the first to show how firm-level technology and demand shocks affect firms' labor adjustments through hires and separations in response to shocks of different nature, signs, and magnitudes. We believe that we are the first to show that firms reduce their labor input though increased separations rather than through reduced hires when hit by a permanent negative idiosyncratic shock. Our finding that transitory demand shocks have a much more limited impact on employment adjustment than permanent demand shocks is, however, fully in line with Guiso, Schivardi, and Pistaferri (2005), who show that firms insure workers' wages relative to transitory (but not permanent) shocks to value added. Perhaps most importantly, we believe that our reduced-form evidence on the importance of idiosyncratic product-demand shocks for worker reallocation should be directly relevant for the theoretical literature on the relationship between firm-level revenue productivity and labor adjustments (e.g., Bentolila and Bertola 1990; Davis and Haltiwanger 1992; Hopenhayn and Rogerson 1993; Mortensen and Pissarides 1994; Cahuc, Postel-Vinay, and Robin 2006; Lise, Meghir, and Robin 2016). This literature tends to emphasize technology shocks as the key

driving force behind labor adjustments, but our results instead suggest that a careful modelling of shocks to the product-market environment is a viable way forward in order to provide a better understanding of the process where workers are reallocated across firms.

The paper is organized as follows. Section 2 outlines a simple model that motivates the long-run restrictions needed to extract our permanent demand and technology shocks. Section 3 introduces the main characteristics of the firm-level data used in the analysis and discusses the empirical implementation of the SVAR and validation of the shocks. Section 4 reports the results on the relationships between net employment, hires, and separations with technology and demand shocks. Section 5 documents how hires and separations respond to positive and negative shocks. Finally, section 6 concludes. Appendices, containing background information and additional results, are published online.

2 Model and Empirical Strategy

2.1 Long-Run Model with Permanent Shocks

In this section, we outline a stylized model of monopolistically competitive firms that allows us to identify two exogenous idiosyncratic driving forces of firms' relative performance: *technology shocks,* which affect firms' physical productivity, and *demand shocks,* which affect firms' ability to sell their products at a given price. The purpose of the paper is to analyze how these two disturbances affect firms' hiring and separation policies. Our approach only requires that we define a set of restrictions that are valid in the long run. The model is therefore deliberately stylized and ignores many factors that may be important for short-run dynamics.[5]

[5] The key distinction between our technology shocks and demand shocks lies in how the shock affects the producing firm, not in the origin of the shock. This approach, which is consistent with the existing (micro) literature (such as Foster, Haltiwanger, and Syverson (2008), and Syverson [2011]), implies that we do not distinguish between shifts in the firm-specific demand curve that arise from changing preferences among final consumers, those that arise from increased demand among downstream firms, and those that arise from quality changes that increase product demand at a given price. Franco and Philippon (2007) label these as shocks to market shares, and model them formally as preference shocks. The firm-level price index we use is based on unit prices for very detailed product codes (8/9-digit Harmonized System/Combined Nomenclature codes), which limits the scope for quality changes to be the key component in our demand shock. However, it is straightforward to show that if we added a quality shock to the system developed below (through a wedge between the measured firm-level price, based on unit values, and the quality-adjusted price),

To identify firm-level structural shocks, we need to make assumptions about the technology and market conditions faced by the firm. Our setup follows Eslava et al. (2004) and Foster, Haltiwanger, and Syverson (2008, 2016) closely, by using a first-order approximation of production technologies and product market demand and modeling the key technology and demand shocks as neutral shifters of the production function and demand curve, respectively. Following these papers, the firm-level production function is approximated by:

$$Y_{jt} = A_{jt} N_{jt}^{\alpha} K_{jt}^{\beta} M_{jt}^{1-\alpha-\beta} \text{ and } \alpha, \beta \in (0,1), \tag{1}$$

where physical gross output Y_{jt} in firm j at time t is produced using technology indexed by A_{jt} and combining labor input N_{jt}, capital input K_{jt}, and intermediate production factors (including energy) M_{jt}. Importantly, our data allow us to account for idiosyncratic firm-specific price changes, so that our measure of technology (the Solow residual, A_{jt}) refers to *physical* total factor productivity (TFPQ), rather than *revenue* total factor productivity (TFPR) in the terminology of Foster, Haltiwanger, and Syverson (2008). Equation (1) presupposes a constant returns technology, which is our baseline assumption. However, in robustness exercises we relax this assumption.

The baseline representation of the firm-level demand curve is a constant-elasticity function

$$Y_{jt} = \left(\frac{P_{jt}}{P_t}\right)^{-\sigma} Y_t \Omega_{jt} \text{ and } \sigma > 1, \tag{2}$$

where P_{jt}/P_t is the firm's relative price, Y_t denotes aggregate market demand, and Ω_{jt} is a firm-specific demand shifter. The parameter σ denotes the elasticity of substitution across products and hence captures the demand elasticity for each firm in the economy. Here, we assume a constant demand elasticity, but below we show that our identification remains valid if we treat σ as a function of the shocks, that is, if $\sigma = \sigma(A_{jt}, \Omega_{jt})$, allowing for Kimball-style (1995) strategic complementarity in price-setting.

Following Guiso, Schivardi, and Pistaferri (2005) and Franco and Philippon (2007), we model the key shocks as permanent shifters. Formally:

$$\begin{aligned} A_{jt} &= A_{jt-1} e^{\mu_j^a + \Phi^a(L)\eta_{jt}^a}, && (3) \\ \Omega_{jt} &= \Omega_{jt-1} e^{\mu_j^\omega + \Phi^\omega(L)\eta_{jt}^\omega}, && (4) \end{aligned}$$

it would enter the system symmetrically to the demand shock.

where μ_j^a and μ_j^ω are constant drifts, and $\Phi^a(L)$ and $\Phi^\omega(L)$ are polynomials in the lag operator, L. The white noise idiosyncratic (orthogonal) technology and demand shocks are denoted by η_{jt}^a and η_{jt}^ω. The assumed functional form implies that the shocks' lag polynomials are linearly related to the log differences of A_{jt} and Ω_{jt}, respectively.[6] As is evident from the formulation, our focus is on permanent shocks, but in a variation of the model we also explicitly analyze the role of transitory disturbances (see Section 4.2).

Our model also allows for a long-run impact of shocks to factor prices other than labor. This is potentially important in the Swedish setting of a small open economy where factor prices are likely to vary across sectors and time (e.g., due to exchange rate volatility). To simplify the notation, we define a price index (consistent with cost minimization) for input factors other than labor, $P_{jt}^F = \left(P_{jt}^K/\beta\right)^\beta \left(P_{jt}^M/\left(1-\alpha-\beta\right)\right)^{1-\alpha-\beta}$, where P_{jt}^K is the price of capital and P_{jt}^M is the price of intermediate materials at time t. Since the empirical specification will include time fixed effects, effectively removing the impact of average market prices, P_{jt}^F will only capture idiosyncratic firm-specific disturbances in factor prices, which, in turn, are assumed to follow a stochastic process of the same form as the demand and technology shocks. Thus, P_{jt}^F evolves according to

$$P_{jt}^F = P_{jt-1}^F e^{\mu_j^f + \Phi^f(L)\eta_{jt}^f}, \tag{5}$$

where μ_j^f is a firm-specific drift; $\Phi^f(L)$ is a polynomial in the lag operator, L; and η_{jt}^f is a white noise factor price shock.

2.2 Identifying Permanent Shocks

2.2.1 Recursive Set of Long-Run Restrictions

As our baseline strategy to identify the shocks of interest, we use the motivating model discussed above to derive a set of recursive relationships regarding how our structural shocks can affect observable variables in the long run. The system allows us to incorporate explicit shocks to factor prices and neutralize disturbances through potential wage shocks.[7]

We first note that the assumptions of the model ensure that the only shock that

[6] This, in turn, provides a convenient representation of the vector autoregression specified below.

[7] In section 2.4, we discuss alternative strategies to identify the shocks that also are consistent with the same motivating model. Reassuringly, our results do not depend on which strategy we use.

can affect the physical gross output Solow residual (A_{jt}) is the technology shock. We then use the standard result that a firm's optimal pricing rule under these conditions is to set the price, P_{jt}, as a constant markup $\sigma/(\sigma-1)$ over marginal cost, MC_{jt}. Denoting wages by W_{jt}, marginal cost in optimum is

$$MC_{jt} = A_{jt}^{-1} \left(\frac{W_{jt}}{\alpha} \right)^{\alpha} P_{jt}^{F}. \tag{6}$$

In equilibrium, $MC_{jt} = \left(W_{jt}N_{jt}\right)/(\alpha Y_{jt})$. This expression, together with equation (6), gives

$$(W_{jt}N_{jt}/Y_{jt})W_{jt}^{-\alpha} = \alpha^{1-\alpha} A_{jt}^{-1} P_{jt}^{F}. \tag{7}$$

Expression (7) will be affected by technology and factor price shocks but not demand shocks. Any direct shocks to the firm-level wage-setting relationship (such as changes in the degree of competition over similar types of labor) will not drive this expression. As the left-hand side of equation (7) shows, this is essentially a measure of unit labor cost ($W_{jt}N_{jt}/Y_{jt}$) net of wage-setting disturbances. We therefore refer to this variable as the wage-neutral unit labor cost ($WNULC_{jt}$).[8]

Using the demand equation (2) and expression (6), we arrive at

$$Y_{jt}W_{jt}^{\sigma\alpha} = \psi Y_t P_t^{\sigma} A_{jt}^{\sigma} \left(P_{jt}^{F}\right)^{-\sigma} \Omega_{jt}, \tag{8}$$

where $\psi = (1/\alpha)^{-\sigma\alpha} \left(\sigma/(\sigma-1)\right)^{-\sigma}$. Thus, expression (8) will be driven by shocks to technology, factor prices other than labor, and demand (apart from aggregate factors, which will be captured by time dummies in the empirical implementation of the model). In effect, expression (8) is output changes adjusted for wage-setting disturbances. We refer to this expression as the wage-neutral demand (WND_{jt}), to highlight that this expression helps us recover the permanent demand shocks.

Table 1, column 1, summarizes the derived recursive system of equations that can all be constructed from our firm-level data as long as we have an estimate of demand elasticity σ (as detailed in the next section). Column 3 summarizes the three key restrictions on which we rely for identification:

1. The measured physical Solow residual ($TFPQ$ in the terminology of Foster et al. 2008) equals A and hence is independent of demand, Ω, and factor prices,

[8] We also experimented with replacing unit labor cost with unit materials cost in equation (7), and refer to Section 4.3 for a discussion of the results. We thank one of the referees for this suggestion.

P^F).[9]

2. The "wage-neutral unit labor cost" ($WNULC$), as defined in the second row, is a function of A and P^F.

3. The "wage-neutral demand" (WND), as defined in the third row, is a function of A, Ω, and P^F.

Table 1: *Core Structural VAR Equations*

	(1)		(2)	(3)
Variable:	Measured in data as:		Model expression:	Long-run restrictions:
$Solow$	$Y_{jt}\left(N_{jt}^{\alpha}K_{jt}^{\beta}M_{jt}^{1-\alpha-\beta}\right)^{-1}$	$=$	A_{jt}	Independent of η^{ω} and η^{f}
$WNULC$	$\left(W_{jt}N_{jt}/Y_{jt}\right)W_{jt}^{-\alpha}$	$=$	$\alpha^{1-\alpha}A_{jt}^{-1}P_{jt}^{F}$,	Independent of η^{ω}
WND	$Y_{jt}W_{jt}^{\sigma\alpha}$	$=$	$\psi Y_t P_t^{\sigma} A_{jt}^{\sigma}\left(P_{jt}^{F}\right)^{-\sigma}\Omega_{jt}$	–

Note: $Solow$ = physical Solow residual (TFPQ), $WNULC$ = wage-neutral unit labour cost and WND = wage-neutral demand, $\psi = \left(\frac{1}{\alpha}\right)^{-\sigma\alpha}\cdot\left(\frac{\sigma}{\sigma-1}\right)^{-\sigma}$.

We will also include a fourth residual variable in the system to soak up all remaining transitory dynamics, as in Franco and Philippon (2007). This prevents any other (residual) transitory dynamics from being mechanically loaded into the demand shock in the third row without changing the long-run properties of the system, since the shock is only allowed to have long-run effects on itself. As a baseline we will use output as the fourth residual variable, but a set of robustness exercises (discussed in Appendix E) shows that the choice of this variable is irrelevant for the main results in the paper.

2.2.2 Implementation of the Long-Run Restrictions

We follow Blanchard and Quah (1989) to implement the long-run restrictions and filter out the permanent shocks of interest. Here, we briefly explain how these restrictions are implemented in practice and refer to Appendix B for details. Consistent with our

[9]This assumption only remains credible if the Solow residual is calculated from a measure of real output where nominal output has been deflated by firm-specific prices. Using instead *sector-level* price deflators (a measure often used in empirical analyses) will make output a function of firm-specific idiosyncratic prices, which themselves are likely to depend on shocks other than technology (see Carlsson and Nordström-Skans (2012) for direct evidence).

postulated stochastic shock processes, we can write the (log difference of the) system outlined in table 1, augmented with the additional transitory variable (output), as a function of all relevant current and past structural shocks. Thus, we have the following vector moving average (VMA) representation (using lowercase letters for logarithms):

$$\Delta \mathbf{x}_t = \mathbf{C}(L)\eta_t, \tag{9}$$

where $\Delta \mathbf{x}_t = [\Delta a_{jt},\ \Delta wnulc_{jt},\ \Delta wnd_{jt}, \Delta y_{jt}]'$ denotes the first differences of our observed variables and $\eta_t = [\eta^a_{jt}, \eta^f_{jt}, \eta^\omega_{jt}, \eta^y_{jt}]'$ denotes the set of structural shocks (with η^y_{jt} being the fourth shock associated with Δy_{jt}). The elements of the four-by-four matrix $\mathbf{C}(L)$ contain polynomials in the lag operator, L, that is, $C_{rc}(L) = \sum_{k=0}^{\infty} c_{rc}(k)L^k$. Cumulated across all lags, k, the $c_{rc}(k)$ parameters provide the long-run impact of the shocks.

Since the technology shock, η^a_{jt}, is the only shock with a long-run impact on a_{jt}, we know that $\sum_{k=0}^{\infty} c_{12}(k) = \sum_{k=0}^{\infty} c_{13}(k) = \sum_{k=0}^{\infty} c_{14}(k) = 0$. Equivalently, we know that only the technology and factor price shocks can have a long-run effect on $wnulc_{jt}$, so $\sum_{k=0}^{\infty} c_{23}(k) = \sum_{k=0}^{\infty} c_{24}(k) = 0$. Finally, since the residual shock has no long-run effects on wage-neutral demand, it follows that $\sum_{k=0}^{\infty} c_{34}(k) = 0$.

Empirically, we estimate a set of reduced-form equations where the first differences of our observed variables are regressed on the lagged vector of the same variables, that is, the vector autoregression(VAR)-representation of (9):

$$\Delta \mathbf{x}_t = \mathbf{A}(L)L\Delta \mathbf{x}_t + \mathbf{e}_t, \tag{10}$$

where the elements of the four-by-four matrix $\mathbf{A}(L)$ contain lag-polynomials, $\mathbf{C}(L)$, and $\mathbf{e}_t$ is a set of reduced-form errors.[10] To recover the structural shocks from the reduced-form errors, we can compare (9) with (10) to see that the reduced-form errors are related to contemporaneous structural shocks through the expression

$$\mathbf{e}_t = \mathbf{c}(0)\eta_t, \tag{11}$$

where $\mathbf{c}(0)$ is the matrix of the contemporaneous parameters in the lag-polynomials $\mathbf{C}(L)$ from the VMA representation. To recover the structural shocks, we then need to estimate $\mathbf{c}(0)$. To this end, we follow standard SVAR protocols and rely on the

[10]Guided by diagnostic tests, the lag length of the VAR is truncated at two in the empirical application.

long-run and orthogonality restrictions together with our estimates of $\Omega = E\mathbf{e}_t^{\prime}\mathbf{e}$ and $\mathbf{A}(L)$ from the VAR (see Appendix B for details).[11]

What matters for precision when extracting the structural shocks from the reduced-form errors is statistical power in the estimation of the VAR parameters $\mathbf{A}(L)$ and covariance matrix Ω. In our setting, we estimate these components using the dynamic panel data methods of Arellano and Bond (1991). Since these methods rely on cross-sectional variation for identification and this dimension is large in our data, we can estimate the components with considerable precision in comparison with standard time-series applications.

2.3 Benefits of the Empirical Approach

The proposed approach offers several advantages. *First*, the zero-impact restrictions in the last column in Table 1 are imposed as *long-run* restrictions, thus only restricting the accumulated effect of the shock over time, that is, the restrictions take the form $\sum_{k=0}^{\infty} c_{rc}(k) = 0$. Hence, we do not make any assumptions about short-run dynamics or transitory measurement errors. Notably, our identification of the technology shocks (η^a) is therefore consistent with changes in inventories, factor utilization, markups, or idiosyncratic input prices altering the Solow residual, as long as these changes are mean-reverting in levels, that is, as long as they do not affect the level of the Solow residual in the long run.

Second, we do not require that all aspects of the motivating model are true, even in the long run. We only require that the impact of the shocks on the three variables ($Solow$, $WNULC$, and WND) measured in Table 1, column 1, does not violate the restrictions listed in column 3 of the same table. These restrictions are consistent with a wider class of models than the one proposed here.[12] A particular possible extension, which for reasons discussed in Section 4.3 will turn out to be useful, is to let the elasticity of demand (and thus the markup) change in response to the shocks, which we can allow for without affecting the long-run restrictions of Table 1.

Third, it is straightforward to incorporate non-constant returns to scale into the model. This is important, since the key assumption for distinguishing technology

[11] When deriving results in terms of elasticities, and to obtain an estimate of the standard deviation of the structural shocks, we use a re-normalized $\hat{\mathbf{c}}(0)$ where each element is divided by its column diagonal element.

[12] The key assumptions are the relevance of the first-order approximation of the production function, monopolistic competition, and that firms behave optimally given the former restrictions.

shocks from demand shocks is that technology shocks alter the physical Solow residual in the long run, whereas other shocks do not. This assumption implies that changes in the scale of operation are not allowed to alter permanently the efficiency of production as measured by TFPQ. The most straightforward reason why this assumption may prove invalid is that firms might use a production technology with non-constant returns to scale. Appendix B.4 modifies the model for the case of non-constant returns to scale. Section 4 shows that the main results in the paper are robust to variations in the returns to scale.

2.4 Comparison with Alternative Identification Schemes in the Literature

Our system approach can be compared with the static single-equation method employed by Eslava et al. (2004, 2010), Foster, Haltiwanger, and Syverson (2008, 2016), and Pozzi and Schivardi (2016). Essentially, these studies derive the Solow residual from the production function (1) and the demand shock from the demand function (2) using an estimate of σ. This approach does not separate transitory and permanent shocks and may be sensitive to transitory deviations from the assumed functional forms. However, we could embed this approach into the one taken here by running a two-variable SVAR system with the Solow residual as the first equation, $Y_{jt}/\left(N_{jt}^{\alpha}K_{jt}^{\beta}M_{jt}^{1-\alpha-\beta}\right) = A_{jt}$, and the demand shock backed out from the demand function (2), $\left(Y_{jt}/Y_t\right)\left(P_{jt}/P_t\right)^{\sigma} = \Omega_{jt}$, as the second equation. In principle, both strategies are equally valid if the motivating model is true and the data are error free, but the approaches differ in how sensitive they are to possible misspecifications in different dimensions. Compared with our baseline formulation, the two-variables alternative relaxes the assumptions about optimal firm behavior. This comes at the expense of having to rely on price data to capture all the shocks to factor inputs and wages when calculating the demand shocks. In contrast, our strategy uses direct measures of wages and unit labor costs to purge the analysis of these input-price disturbances. We explore this two-equation system in the robustness section (4.3) and, reassuringly, the results are very similar.[13]

The standard approach in the literature is to orthogonalize the structural shocks by using the Solow residual as an instrument of the demand equation when estimating σ.

[13] We thank one of the referees for suggesting this exercise.

The orthogonalization is also imposed in our identification scheme. However, Forlani et al. (2016) allow for a correlation between demand and technology processes and find it to be strongly negative.[14] We allow for firm fixed effects in our empirical setup, which would remove the impact of persistent decisions related to the business model of the firm. For example, the choice of market segment may involve a trade-off between demand and technological efficiency generating a negative relationship between technology and demand. This would be factored out by the introduction of firm fixed effects in the econometric model.

Hottman, Redding, and Weinstein (2016) develop a structural framework to decompose the firm size distribution in terms of the contributions of the heterogeneity of demand, product scope, marginal cost, and markup. Apart from the difference in focus, a key difference is that their structural framework only relies on price and quantity data, whereas our approach (and all the other studies referenced above), uses factor input data as well to identify technology (or marginal-cost) shocks.

Guiso, Schivardi, and Pistaferri (2005) decompose shocks to firm-level value added into permanent and transitory components under assumptions of the stochastic processes underlying the shocks. We share with them the accent on the permanent versus transitory nature of the shocks. Aside from the differences in the questions posed, Guiso, Schivardi, and Pistaferri (2005) do not have data on firm-level prices and hence cannot provide a structural interpretation of the shocks, as is possible here.

3 Data and Estimation of the Shocks

3.1 Data on Firms

Our primary data sources are the Swedish Industry Statistics Survey (IS) and the Industrins Varuproduktion (IVP). These data sets contain annual information on inputs, outputs, and firm-specific producer prices for Swedish manufacturing plants from 1990 through 2002. The data have complete coverage of all plants, except for plants with fewer than 10 employees, which are subject to random sampling. We therefore exclude all plants with fewer than 10 employees and provide robustness checks to verify that our analysis is robust to endogenous transitions below this threshold. We perform our analysis at the plant level, but because about 72 percent of the observations in our

[14]See also Hottman, Redding, and Weinstein (2016) and Eslava and Haltiwanger (2018).

sample pertain to plants that are also firms, we refer to the plants as firms.

An important part of our data is the firm-specific price index built from plant-specific unit price changes.[15] These data allow us to derive a measure of gross output that is robust to changes in relative prices across firms, similar to Eslava et al. (2004) and Smeets and Warzynski (2013). Details about data construction are presented in Appendix A. The data entering the VAR model cover 6,137 firms and 53,379 firm-year observations, but since the VAR model uses lags, we can extract structural shocks for 41,105 firm-years.

Table 2: *Summary Statistics: Firm Data*

		(1)	(2)	(3)	(4)	(5)	(6)
	Category	Mean	S.d.	p(25)	p(75)	Firms	Observations
Output growth	Overall	0.029	0.190	-0.073	0.133	6,125	40,451
	Within		0.175				
Price growth	Overall	0.022	0.069	-0.001	0.044	6,125	40,451
	Within		0.064				
ΔSolow	Overall	0.001	0.112	-0.062	0.062	6,125	40,451
	Within		0.106				
$\Delta wnulc_{jt}$	Overall	0.010	0.155	-0.077	0.097	6,125	40,451
	Within		0.147				
Δwnd_{jt}	Overall	0.064	0.224	-0.060	0.189	6,125	40,451
	Within		0.210				

Note: The "within"rows show the dispersion within establishments. p(N) denotes the Nth percentile of the data.

The top two rows in table 2 describe gross output and price growth in the sample used for the final analysis. The average price change of 2.2 percent per year coincides with the average growth rate of the official producer price index for industry provided by Statistics Sweden. However, in the empirical analysis, all the aggregate trends are accounted for by time dummies (sector-by-time dummies in some robustness exercises). The table also shows the distribution statistics of the main variables used in the analysis, overall and within firms.

[15] The index uses Paasche-type links constructed from survey information on reported sales and volume at the goods level.

3.1.1 Variables in the VAR

Letting lowercase letters denote logs, firm-level changes in the physical Solow residual for firm j at time t are computed as follows:

$$\Delta a_{jt} = \Delta y_{jt} - \Delta z_{jt}, \tag{12}$$

where Δy_{jt} is the growth rate of real gross output, and Δz_{jt} is a cost-share-weighted input index defined as $C_k \Delta k_{jt} + C_n \Delta n_{jt} + C_m \Delta m_{jt}$. The terms Δk_{jt}, Δn_{jt}, and Δm_{jt} are the growth rates of capital, labor, and intermediate materials and energy, respectively, while C_K, C_N, and C_M are the corresponding cost shares in total costs (see details in appendix A). We approximate the cost shares by revenue shares, which should be innocuous since pure profits are small in Swedish manufacturing firms.[16] Moreover, we use industry-level averages over time and take total costs as approximately equal to total revenues.[17] Since cost/revenue shares sum to one, the share for capital is given by one minus the sum of the revenue shares of labor and materials, which we measure from the data. Using data on factor compensation, changes in output, and changes in inputs, we can thus calculate the residual Δa_{jt}, which provides an estimate of changes in the physical Solow residual. This might not accurately measure technology shocks (η^a), due to varying factor utilization, inventories, or truly idiosyncratic factor prices, but the SVAR will filter out true technology shocks from equation (12) as long as η^a is the only factor that permanently shifts A_{jt}. Material inputs are deflated using three-digit sectoral price indices, which implies that we allow not only for an arbitrary set of transitory factor price shocks, but also for permanent input price shocks in the manufacturing sector as long as these are shared with other similar (at the three-digit level) firms. Summary statistics of the Solow residual are found in the third row in Table 2.

[16] Our monopolistic competition model implies pure economic profits. However, similar to U.S. evidence discussed in Basu, Fernald, and Shapiro (2001), we find a very small average (1968-93) share of economic profits (-0.001) when relying on the aggregate Swedish manufacturing data from Carlsson (2003). This finding thus supports the commonly used approximation in the literature of measuring (average) cost shares by (average) revenue shares, which is also used here. For simplicity, however, we do not complicate the cost structure in our model, to accommodate explicitly the absence of economic profits in the data.

[17] Treating cost/revenue shares as constant over time is sensible given that the approach we take is not sensitive to transitory variation. Moreover, trying to account for time variation in output elasticities is complicated, because observed factor payments might not be allocative period-by-period, for example, because of implicit contracts.

To compute $\Delta wnulc_{jt}$ we rely on cost minimization and use C_N as the estimate of α, letting it vary by two-digit industry. The rest of the components of $\Delta wnulc_{jt}$ are directly observed in the firm-level data. The fourth row in Table 2 shows the distribution of $\Delta wnulc_{jt}$.

The computation of Δwnd_{jt}, requires an estimate of the demand elasticity σ. We obtain this by estimating the demand equation (2) using the Solow residual to instrument the firm idiosyncratic price, as in Foster, Haltiwanger, and Syverson (2008). The instrument is consistent with our initial assumptions, because the Solow residual is expected to affect firm-level sales only through firm-level prices. The results of this procedure suggest an elasticity of substitution equal to 3.306 (s.e. 0.075). The estimate of σ is well in line with standard calibration exercises (see, e.g., Erceg, Henderson, and Levin 2000) as well as Swedish micro-evidence provided by Heyman, Svaleryd, and Vlachos (2013). As robustness checks, we also show that the main results are robust to using sector-specific estimates of σ and a very wide span of assumed values of σ. The ensuing measure of Δwnd_{jt} is provided in the final row in Table 2.

3.2 Data on Labor Flows

To analyse the impact of the shocks on the use of labor and flows into and out of the firms, we link a longitudinal employer-employee database (Statistics Sweden's register-based labor market statistics, or RAMS) to the firm-level data. These data are based on tax records and include the identity of all employees in each firm. Following Carlsson, Messina, and Nordström-Skans (2016) and others, we measure employment in November each year and restrict the (main) analysis to full-time employees in their main jobs.[18] In the end, we are able to match shocks and labor flows for 40,451 firm-year observations in 6,125 firms. The final sample covers nearly two-thirds of all manufacturing employees.[19] For completeness, we further study how the use of

[18] More precisely, our raw annual data include information on all employment spells (even with annual earnings corresponding to a few kronors) and include information on the identity of the employer, the employee, total annual earnings, as well as the first and last remunerated months during the year. Following Nordström Skans, Edin, and Holmlund (2009), and similar in spirit to Song et al. (2019), we only include employment spells where average monthly earnings exceed 75 percent of the monthly minimum wage and the spell covers November. In auxiliary exercises, we separately study the dynamics of all those employment spells that are excluded due to these restrictions.

[19] The employment data that were used to construct the variables in the VAR were obtained from a different source (IS) than the employment, hiring, and separation data used in the final analysis (which were obtained from RAMS). This insulates the analysis from the threat of joint measurement

marginal workers (i.e., employees who do not satisfy these criteria) changes in response to the shocks.

We measure employment in logs or, when decomposing the results into flows, we measure net employment changes using the metrics proposed by Davis, Haltiwanger, and Schuh (1996). Thus, net employment growth is defined as the change in employment relative to the preceding year, divided by the average employment during the two years. Similarly, we define the hiring (separation) rate as the number of new (separated) employees between t and $t-1$, divided by the average number of employees during the two years. With these definitions, net employment growth will be the difference between the hiring rate and the separation rate, and the timing of the flows is defined such that the employment flow equation holds, that is, $Employment_t = Employment_{t-1} + Hires_t - Separations_t$.

Table 3: *Summary Statistics: Worker Data*

	Category	(1) Mean	(2) S.d.	(3) p(25)	(4) p(75)	(5) Firms	(6) Observations
Net employment rate	Overall	0.012	0.208	-0.062	0.089	6,125	40,451
	Within		0.195				
Hiring rate	Overall	0.150	0.151	0.063	0.200	6,125	40,451
	Within		0.127				
Separation rate	Overall	0.138	0.152	0.061	0.174	6,125	40,451
	Within		0.131				
ST separation rate	Overall	0.061	0.082	0	0.083	6,125	40,451
	Within		0.065				
Marginal net emp. rt.	Overall	0.009	0.353	-0.069	0.082	6,125	40,451
	Within		0.334				

Note: The "within"rows show the dispersion within establishments. p(N) denotes the Nth percentile of the data.

We do not observe the contract type in the data, but to explore the role played by the (potential) flexibility provided by marginal workers, we use two additional flow margins. We i) define the short-tenure (ST) separation rate as the number of separations of short-tenure (fewer than three years, constituting 23 percent of all worker-year observations) workers divided by average employment across the two years, and ii)

errors in the calculation of the shocks and the employment adjustment analysis. However, the estimates of the impact of the shocks on overall employment are very similar using the two data sources, suggesting that the issue is of minor importance.

measure the change in the number of marginal workers, who are defined as individuals who are employed during the year but not in November, and hence are not included in the stock of end-of-year employees.

Descriptive statistics are presented in Table 3. The average hiring rate during the observation period is 15 percent, and the average separation rate is 14 percent, of which slightly less than half (6 percent) are separations of short-tenure workers.

3.3 Estimation and Validation of the VAR

To derive the shocks of interest, we estimate an SVAR on the three variables defined in Table 1, Δa_{jt}, $\Delta wnulc_{jt}$, and Δwnd_{jt}, and the fourth residual variable, Δy_{jt}. Details on the estimation, distribution of the shocks, and impulse responses are provided in Appendix B. We find that the standard deviation of the demand shock is about 60 percent larger than that of the technology shock (16.2 and 10.1, respectively). The impulse responses of the four variables to the two shocks display fairly limited dynamics, generally converging to the long-run equilibrium within a year. This is particularly the case for the Solow residual, which suggests that much of the dynamics in standard measures of Solow residuals that use sectoral prices to deflate output may be due to the dynamics of idiosyncratic prices (see Carlsson and Nordström-Skans (2012) for direct evidence on relative price dynamics).

Appendix B.2 provides internal support for the interpretation of the shocks based on theory-consistent signs for the three unrestricted responses within the VAR system. The estimated VAR model does not impose any restrictions on how technology shocks affect WNULC and WND, but, as predicted from the model, WNULC falls permanently and WND increases in response to a (permanent) positive technology shock. And in line with the model, positive factor price shocks lead to a reduction in WND.

In Appendix B.3, we further validate the interpretation of the derived shocks by showing that they have the expected qualitative impacts on firm-specific prices and output. From theory, we know that technology and demand shocks should affect output. The response of prices instead depends on the nature of the shock. A positive technology shock lowers the cost of production, so firms need to lower their prices to increase their sales along a fixed demand curve. Instead, demand shocks shift the firm-specific demand curve, allowing the firm to sell more at constant prices. The appendix validates these predictions: a one standard deviation technology (demand)

shock increases output by 6 (10) percent in the long run. Moreover, as expected, prices decrease significantly due to technology shocks, but they increase marginally when hit by demand shocks. These results are not imposed from the construction of our variables. In particular, prices could well (from a pure measurement standpoint) respond in either direction to structural innovations in technology and demand.

4 Shocks and Employment Adjustments

4.1 Main Results

Figure 1 shows impulse responses of log employment with bootstrapped confidence bands from the VAR when using log employment change as the fourth variable. The results show that idiosyncratic demand shocks have a substantially greater impact than the corresponding technology shocks on firm-level labor adjustments. A positive demand shock of one standard deviation increases employment by slightly more than 6 percentage points, whereas the impact of an equivalent technology shock has a very limited impact on employment. It is also evident from Figure 1 that the dynamics of labor adjustments are fairly limited. More than 90 percent of the long-run adjustments in response to the permanent shocks occur within the first year.

The objective of our analysis is to illustrate how job and worker flows respond to permanent shifts in idiosyncratic production functions and demand curves. To explore departures from linearity and potential asymmetries in the response margins (see Section 5), it is useful to extract the measures of structural shocks from the SVAR and relate them in standard regression frameworks to different outcomes. Thus, this is how we proceed in most of the analyses we present in the paper. Our point of departure is the following baseline specification:[20]

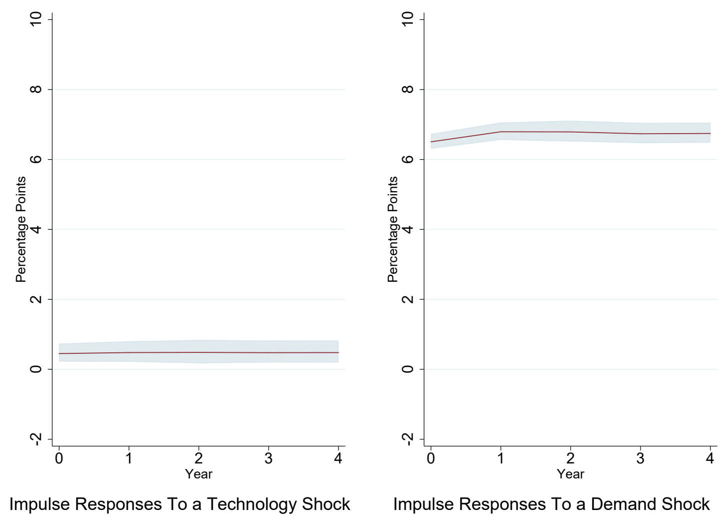
$$Outcome_{jt} = \eta^{a}_{jt}\delta_1 + \eta^{\omega}_{jt}\delta_2 + \rho_t\beta_\rho + \mu_j + \xi_{jt}, \tag{13}$$

where *Outcome* denotes employment (or some measure of labour flows) for firm j at time t. The coefficients δ_1 and δ_2 capture the impact of the two structural shocks.[21]

[20]In Appendix B.5, we derive the long-run structural representations of the relationship between the shocks and our main outcomes under different structural assumptions.

[21]Formally, the inference is exposed to potential generated regressor bias leading to attenuation and underestimated standard errors. However, all the key results are quantitatively unchanged when estimating them internally in the VAR or relying on an instrumental variable strategy (see below),

Figure 1: *Employment Responses*



Note: The values are impulse responses to a one stanrard deviation shock expressed in percentage points. The x-axis denotes years since the shock. Lines depict the mean of the bootstrap distributions. Shaded areas depict the bootstrapped 95 percent confidence intervals calculated from 1,000 replications.

Moreover, we include time, ρ_t, and firm fixed effects, μ_j. The latter allows for drift terms in accordance with the stochastic process for the shocks postulated in section 2.1. The time fixed effects ensure that identification is driven by idiosyncratic, rather than aggregate, shocks.[22]

The long-run effects are estimated by adding additional lags of the structural shocks and summing the estimated coefficients. Using the variables included in the VAR as outcomes, the linear equation (13) augmented with the lags recovers the VMA parameters in equation (9). In practice, as we discussed in the context of the SVAR estimation and elaborate further below, the dynamic responses to permanent idiosyncratic shocks are fairly limited, and adding only one lag summarizes the long-run effect.[23]

Our baseline specification, following equation (13), is presented in Table 4. Column 1 focuses on changes in net employment (defined as in Davis, Haltiwanger, and Schuh

both of which are insensitive to generated regressor biases. This is because the VAR is estimated with considerable precision using panel data, which minimizes the effects of the generated regressor biases.

[22] Since the shocks are identified as structural orthogonal innovations, they are uncorrelated with each other conditional on the year and firm fixed effects of the SVAR.

[23] That is, the coefficients on additional lags are small and insignificant.

[1996]). As expected, the results are very similar to those presented in figure 1. The effect of a normal (one standard deviation) technology shock is 0.11 (not statistically different from 0). If we add one lag of the shocks to the regression and calculate the long-run employment responses (column 4), we find that a one standard deviation technology shock increases employment by 0.4 percentage points, the effect being statistically significant. Instead, demand shocks are the main drivers of employment adjustments: a positive one standard deviation shock to the demand curve increases employment by 5.6 (6) percentage points in the short (long) run. The small differences between the short- and long-run effects corroborate the limited dynamics found in the SVAR framework. Table 4, panel B, instead shows estimates in the form of elasticities (see Appendix B on the computation of the elasticities). The conclusions are very similar.

Table 4: *Contemporaneous and Long-Run Effects on Labour Flows*

	SHORT RUN			LONG RUN		
	(1) NER	(2) HR	(3) SR	(4) NER	(5) HR	(6) SR
A) Responses to a one standard deviation shock:						
Technology (η^a)	0.115	-0.050	-0.165*	0.412*	-0.093	-0.504**
	(0.119)	(0.075)	(0.078)	(0.163)	(0.116)	(0.128)
Demand (η^ω)	5.609**	2.906**	-2.703**	6.009**	3.125**	-2.884**
	(0.173)	(0.096)	(0.120)	(0.228)	(0.156)	(0.186)
B) Elasticities:						
Technology (η^a)	0.011	-0.005	-0.016*	0.0409*	-0.009	-0.050**
	(0.012)	(0.007)	(0.008)	(0.016)	(0.011)	(0.013)
Demand (η^ω)	0.347**	0.180**	-0.167**	0.371**	0.193**	-0.178**
	(0.011)	(0.006)	(0.007)	(0.014)	(0.010)	(0.012)
Observations	40,451	40,451	40,451	34,414	34,414	34,414
Firms	6,125	6,125	6,125	6,116	6,116	6,116

Note: Robust standard errors are in parentheses. NER: Net employment rate; HR: Hiring rate; SR: Separation rate. Hiring and separation rates are measured as the flow between the end points of two years divided by the average employment across these two points in time. The net employment rate is the difference between the hiring rate and the separation rate. The regressions include time dummies and firm fixed effects. The long-run impact is based on the sum of the contemporary effect and the effect of the first lag. ** and * denote statistical significance at the 1 and 5 percent levels, respectively.

We proceed by estimating equation (13) for hires and separations. The results

(Table 4, columns 2 and 3) show that a one standard deviation demand shock increases the hiring rate by 2.9 percentage points and reduces the separation rate by 2.7 percentage points in the short run (slightly more in the long run, as shown in columns 5 and 6). These numbers should be compared with average hiring and separation rates of about 14 to 15 percent each, as shown in Table 3. Thus, the estimates imply that 52 percent of the net employment adjustment is obtained using the hiring margin, and 48 percent using the separation margin. On average, firms rely as much on variations in separations as on variations in hires when responding to the shocks. The results further imply that the low response of net employment to technology shocks does not mask any substantive counteracting responses of gross worker flows. Rather, idiosyncratic technology shocks appear to have a limited impact on hiring and separation rates in the short and long run.

Next, we isolate the analysis of separations of short-tenure workers, which constitute 23 percent of the worker-year observations in the sample. The results in table 5, column 2, show that these make up slightly more than one-third of the total separation response to demand shocks in the short run (column 1) and even less in the longer run (column 4 versus column 5). The lower relative contribution of short-tenure separations in the long run is consistent with a reduction in contemporary hires, which reduces the number of short-tenure workers who can be released in the next period. As a final analysis, we document the responses in terms of "marginal workers," defined as short-term workers who are hired within the year but are not present in November, and thus were not classified as regular workers.[24] The results, presented in Table 5, show that the adjustments in marginal workers are very similar to the adjustments in regular employees in the sense that most of the adjustment is due to demand shocks. We also see some evidence of overshooting, in the sense that the short-run response in the use of marginal workers (3.8 percent of the number of full-time employees) is larger than the long-run adjustment (3 percent).

Overall, our main results show that i) the responses of employment and labor flows are much stronger to permanent demand shocks than to permanent technology shocks; ii) most labor adjustments happen within the year; iii) hires and separations are equally important as adjustment margins; and iv) short-tenure separations and adjustments of marginal workers follow similar adjustment patterns as regular em-

[24]We measure the *number* of marginal employees and do not address the intensity with which these are used.

Table 5: *Contemporaneous and Long-Run Effects on Short-Tenure Separations and Marginal Workers*

	SHORT RUN			LONG RUN		
	(1) SR	(2) STSR	(3) MNER	(4) SR	(5) STSR	(6) MNER
Technology (η^a)	-0.165*	-0.117**	0.110	-0.504**	-0.177**	0.482
	(0.078)	(0.038)	(0.162)	(0.128)	(0.066)	(0.248)
Demand (η^ω)	-2.703**	-1.010**	3.796**	-2.884**	-0.416**	3.019**
	(0.120)	(0.052)	(0.213)	(0.186)	(0.076)	(0.278)
Observations	40,451	40,451	40,451	34,414	34,414	34,414
Firms	6,125	6,125	6,125	6,116	6,116	6,116

Note: Values are the effect of a one standard deviation shock. SR: Separation rate; STSR.: Short-tenure separation rate, measured as the number of separations of short-tenure (¡ 3 years) workers; MNER: marginal net employment rate, refers to workers who do not fulfill the criteria for full-time primary employment, but are employed by the firm at time t. All rates are measured as the flow between the end points of two years divided by the average (full-time primary) employment across these two points in time. The regressions include time dummies and firm fixed effects. The long-run impact is based on the sum of the contemporary effect and the effect of the first lag. Robust standard errors are in parentheses. ** and * denote statistical significance at the 1 and 5 percent levels, respectively.

ployees, but with a somewhat larger initial response.

4.2 Transitory Shocks

The focus of the analysis so far has been on how firms adjust employment, hires, and separations when hit by *permanent* idiosyncratic shocks. Here we instead derive an alternative measure of demand and technology shocks that also includes transitory disturbances. For technology shocks, we simply use the observed (physical) Solow residuals. For demand shocks, we use the residuals from estimation of a log-linearized version of the demand equation (2). This regression includes time dummies to control for aggregate shocks and firm fixed effects to eliminate between-firm permanent heterogeneity. Because prices are endogenous in the regression, we use the Solow residuals as instruments. Since the ensuing residuals of the estimated demand equation represent changes in sales without price adjustments, they serve as a measure of demand shocks. This strategy to derive demand and technology shocks is similar to

that of Foster, Haltiwanger, and Syverson (2008). Thus, we label these shocks "FHS."

In contrast to our SVAR filter, the (static) FHS procedure does not differentiate between permanent and transitory shocks, and the processes do not account for factor price shocks. The correlation between the FHS demand shocks and our baseline SVAR demand shocks is 0.538. The standard deviation of the FHS demand shocks is considerably higher than in the baseline SVAR (0.24 versus 0.16). Thus, the two demand shock series appear to contain a substantial common component without being identical. The correlation between the FHS demand shocks and the factor price component of the SVAR is considerably smaller (-0.25), but it is statistically significant. As expected, the FHS demand shocks are uncorrelated with the SVAR technology shocks. And, as expected given the limited dynamics observed in the physical Solow residual series, the physical Solow residual is highly correlated with the SVAR technology shocks (0.98), and only marginally related to our SVAR demand shocks (correlation of 0.02) and SVAR factor price shocks (correlation of 0.06).

Table 6: *Baseline Estimates versus Solow Residuals and FHS Demand Shocks for Log Employment*

	SHORT RUN			LONG RUN		
	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	FHS	Transitory	Baseline	FHS	Transitory
Technology (η^a)	0.153	0.333*	-0.157	0.504*	0.993**	0.0754
	(0.159)	(0.168)	(0.164)	(0.214)	(0.250)	(0.216)
Demand (η^ω)	5.986**	3.406**	0.674**	6.357**	4.061**	0.863**
	(0.233)	(0.183)	(0.136)	(0.310)	(0.252)	(0.217)
Observations	40,451	40,451	40,451	34,414	34,414	34,414
Firms	6,125	6,125	6,125	6,116	6,116	6,116

Note: Values are the effect of a one standard deviation shock. In the FHS columns the technology shock is the Solow residual, and the demand shock is FHS demand, as defined in the main text. The transitory shocks are calculated as the residual component of the FHS series. Robust standard errors are in parentheses. The regressions include time dummies and firm fixed effects. The long-run impact is based on the sum of the contemporary effect and the effect of the first lag. ** and * denote statistical significance at the 1 and 5 percent levels, respectively.

Table 6 shows how these measures relate to labour flows. The estimates with our SVAR shocks are reproduced in columns 1 and 4 for comparison. Clearly, the main findings hold when using the FHS series (columns 2 and 5): the short-run impact of the demand shocks is 10 times that of the technology shock in the short run, and

about four times in the long run. But it is also noticeable that the estimated impact of the demand shocks is about half as large when using FHS demand as when using the SVAR demand shock.

To see what drives the difference, we proceed by purging the FHS series of our permanent structural shocks. To this end, we run a regression with the FHS demand as the dependent variable and use our SVAR shocks (demand, technology, and factor prices) as regressors and then repeat this for the Solow residual. We label the residuals of this exercise *transitory* demand and technology shocks. Because these residuals are measured in the same units as the composite FHS demand and technology shocks, we can directly compare their impacts on employment adjustments.[25]

The results, in table 6, columns 3 and 6, show that the ensuing transitory demand shocks have a much more muted impact on employment than the SVAR and composite FHS shocks. This reinforces the idea that our SVAR strategy captures the most relevant determinants of labor adjustments. The result holds for the short- and long-run responses. That the long-run response to transitory demand shocks does not revert back when the lag is introduced suggests that the transitory series may still contain a persistent component.[26] With this caveat in mind, that the part of the demand series that is certified to be permanent has a much larger effect suggests that firms' employment adjustment depends on the time-series properties of the shocks, as in Franco and Philippon (2007); Roys (2016); and Guiso, Schivardi, and Pistaferri (2005).

4.3 Robustness

We have carried out a an extensive battery of checks to assess the robustness of our claims that i) firm-level demand shocks are more important in the determination of labor adjustments than firm-level technology shocks, and ii) employment adjustment to the permanent shocks is very rapid with limited short-term dynamics. To conserve space, we defer discussions about basic specification checks such as variations in the demand elasticity, sample selection, using an alternative fourth variable, and variations based on alternative VAR specifications to our online appendix E. Here, we

[25]The decomposition resembles that in Guiso, Schivardi, and Pistaferri (2005), which extracts the permanent component of firm-level value added using high-order polynomials of lags as instruments. Although the mechanics of the methods differ, the underlying logic is similar.

[26]If we partial out the series with the residual shock of the SVAR $\left(\eta_{jt}^{y}\right)$, the estimates are about half the size and the long-run estimate is nonsignificant.

focus on those exercises that contain more economic intuition.

Returns to scale. The constant returns to scale (RTS) assumption used in the construction of the Solow residual is potentially controversial. In Carlsson, Messina, and Nordström-Skans (2016), we estimate RTS separately for the durables and non-durables sectors among Swedish manufacturing firms, obtaining 1 for durables and 0.9 for non-durables. In both cases, we cannot reject the null of constant RTS. These results are very similar to what Basu, Fernald, and Kimball (2006) report for the United States. What matters is the long-run RTS, which implies that the theoretical case for assuming constant RTS becomes stronger. To assess the robustness of the results to this assumption, the model can be altered to accommodate increasing or decreasing RTS. This affects the measures that are fed into the SVAR (for details, see Appendix B.4) and hence also the estimated magnitudes of employment adjustments. However, the main conclusions from the baseline analysis are not altered. Table E1, column 2, shows that a positive technology shock of one standard deviation raises employment by 1 percentage point in the short run (1.4 in the long run, see column 5) when the Solow residual is constructed using 0.9 RTS. But this estimate remains far below the estimated impact of a demand shock: an increase of 6.1 percentage points in the short run and 6.3 percentage points in the long run. If instead we impose an RTS coefficient of 1.1, the results change in the other direction (the impact of technology turns negative), but the main message for the strong relative importance of demand remains unaltered.[27]

Sectoral heterogeneity. The dynamic panel approach used for estimation took advantage of our large-N, small-T panel setting to estimate the VAR system with considerable precision. This is a key advantage relative to standard SVAR estimations in the macro literature. However, a potential cost is that the underlying dynamic processes are assumed to be equal across different types of firms. To address this concern, we have allowed for separate dynamics for each two-digit industry, and the employment adjustment results remain unchanged (see Appendix Table E2, column

[27] An alternative robustness exercise would be to estimate production functions with one of the many proposed estimators in the literature (for example, following Olley and Pakes (1996)). However, this would only matter in practice if the output elasticities were very different from the cost shares, and this would certainly be a cause for concern since it would require that the overall returns to scale fell outside reasonable bounds. This is why we choose to use the cost shares (measured as revenue shares) directly and instead provide robustness exercises over the returns to scale. Given that the overall results are robust to these variations, relying on any sensible production function estimates would not change our results.

6). Demand shocks have a much larger impact on employment adjustment than technology shocks do.

Firm exit. A possible concern with the analysis is that we disregard the firm exit process. Firms are likely to exit in response to severe negative demand or technology shocks, and this process may impact labour dynamics. Furthermore, we lose coverage in the IS firm-level data when firms shrink below 10 employees. To address these concerns, we analyze the employment impact of the shocks using a two-period specification instead of the one-period baseline. In the baseline, we evaluate employment changes between t and $t-1$ divided by average employment over the two years. The new specifications change the numerator, which is now defined over changes between $t+1$ and $t-1$. Since labor flows are defined even if all workers exit the year after the shock, and because we can measure employment also when firms fall below 10 employees in the RAMS data, we can calculate the impact of the shocks excluding or including the firms that fall below the threshold (or exit entirely) in $t+1$. Reassuringly, the results are insensitive to whether we include or exclude these observations (see Appendix Table E6).[28]

Endogenous demand elasticities. The difference in employment responses between permanent demand and technology shocks should be understood in a context where the two types of shocks have similar empirical relationships to output, and where technology affects prices much more forcefully than demand shocks do. Qualitatively, these patterns are thus all well in line with what is expected from our motivating model presented in section 2. But in the model, the magnitudes of the employment, output, and price responses to the two shocks are all tightly determined by a (constant) value of σ (see Appendix B.5 for the full Jacobian). Unsurprisingly, the magnitudes of the empirical (long-run) responses of employment, prices, and output to those shocks do not concur with a single constant value of σ. For example, employment responses to technology and demand shocks in the model are related by a factor of $\frac{1}{\sigma-1}$, which, given the long-run responses of employment (shown in Figure 1), would imply a value of σ of about 1.1. Instead, the output and price responses to technology shocks (shown in Figure B5) suggest a value of $\sigma = 3.3$ (see the discussion in Appendix B.5). Although we show in the appendix that we can choose any reasonable number for σ without affecting the results, we cannot satisfy the full set of responses in output, prices, and

[28] We have also analysed the explicit relationship between the shocks and the probability of firm exit from the sample. The main driver of firm exits is large negative demand shocks, which is well in line with the results for the United States in Foster, Haltiwanger, and Syverson (2008).

employment with any single value of σ. The data thus seem to ask for a model that is richer in its description of product market responses to the shocks, although the assumption of a constant σ is one we share with most of the literature.[29] Fortunately, this apparent anomaly can be resolved by a straightforward generalization of the model, allowing the elasticity of demand (and thereby the markup) to be a function of the shocks, that is, allowing for $\sigma = \sigma(A_{jt}, \Omega_{jt})$, in the spirit of Kimball (1995). This replaces equation (2) by

$$Y_{jt} = \left(\frac{P_{jt}}{P_t}\right)^{-\sigma(A_{jt},\Omega_{jt})} Y_t \Omega_{jt},\ \ \sigma(A_{jt}, \Omega_{jt}) > 1 \text{ and } \sigma(\bar{A}_{jt}, \bar{\Omega}_{jt}) = \sigma, \tag{14}$$

where an upper-bar denotes an average across firms. The only change relative to the measurement equations outlined in table 1 of section 2 is that WND acknowledges that σ is no longer constant. The modified model-expression is thus

$$WND = \psi(A_{jt}, \Omega_{jt}) Y_t P_t^{\sigma(A_{jt},\Omega_{jt})} A_{jt}^{\sigma(A_{jt},\Omega_{jt})} \left(P_{jt}^F\right)^{-\sigma(A_{jt},\Omega_{jt})} \Omega_{jt}. \tag{15}$$

This extension is fully consistent with our long-run restrictions. The extension is discussed in detail and quantified in Appendix B.5. The quantification shows that the derivatives of σ to reconcile the joint responses of output, prices, and employment to the two shocks are quite modest. The implied values of σ in response to an interval of ± 1 standard deviation technology shocks is $[2.7, 3.9]$ and for demand shocks the corresponding interval is even tighter, at $[3.2, 3.4]$.

5 Asymmetries and Worker Flows

This section provides an analysis of how firm-level employment adjustments of different signs and magnitudes in response to permanent demand shocks translate into worker flows.[30] This analysis is similar in spirit to that of Abowd, Corbel, and Kramarz (1999) and Davis, Faberman, and Haltiwanger (2012), who provide decomposition exercises on the relative contributions of various worker flows to positive and negative changes in net employment within French and U.S. firms, respectively. In

[29] Including, for example, Foster, Haltiwanger, and Syverson (2008, 2016) and Pozzi and Schivardi (2016).

[30] We focus on permanent demand shocks because technology shocks are found to have negligible impacts on net employment.

contrast to these decompositions, we analyze adjustments due to a well-defined permanent shock. This provides a causal layer to the analysis, which is potentially important since short-run employment fluctuations may be caused by worker flows (i.e., exits or unsuccessful hiring attempts may lead to fluctuations in employment). Using our structural demand shocks as instruments for employment adjustments ensures that the analysis is immune to such reverse causality.

First, however, we characterize the potential asymmetries in net employment adjustments in response to the shocks by replacing the linear terms η^a_{jt} and η^ω_{jt} in equation (13) with two second-order polynomials, one for positive values and one for negative values.[31] Figure 2 documents how the shocks affect the change in employment ($\Delta Employment_{jt}$) using this functional form.[32] For completeness, we show the responses to technology and demand shocks but focus our attention on the demand shock responses. The demand shocks have a similar, almost linear, relationship to employment adjustments on both sides of zero. The net change in employment in response to a one standard deviation positive demand shock (6 percentage points) is reasonably close to the response to a one standard deviation negative shock (-7 percentage points) in absolute values. The differences at the endpoints of very large (± 2 standard deviations) shocks are somewhat more pronounced (9 versus -13 percentage points).[33]

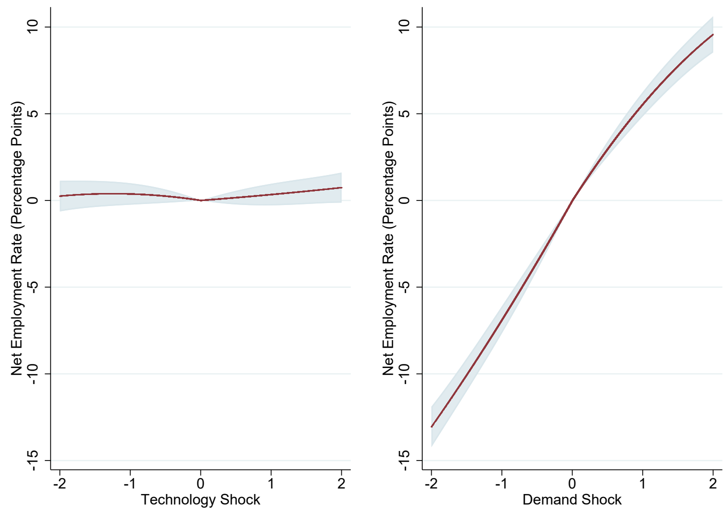
Next, we analyze the potentially asymmetric use of hiring and separations as adjustment margins in response to positive and negative changes in net employment due to demand shocks. To this end, we use an instrumental variables (IV) approach where demand shocks serve as instruments for employment adjustments. We thus replace η^a_{jt} and η^ω_{jt} in equation (13) with a two-sided second-order polynomial of employment changes and instrument these by a corresponding polynomial for the demand shocks (see Appendix C). The IV strategy allows us to see the relative contribution of hiring (versus separation) to employment adjustments as a function of the sign and magnitude of the induced employment adjustment. Due to the underlying identity ($\Delta Employment_{jt} = Hiring_{jt} - Separations_{jt}$), we only show estimates on the im-

[31] Using shorthand for the indicator function $I^+_x = I(x_{jt} > 0)$, we include in the regressions $G(x_{jt}) = g_1 I^+_x x_{jt} + g_2 I^+_x x^2_{jt} + g_3(1 - I^+_x)x_{jt} + g_4(1 - I^+_x)x^2_{jt}$ for each of the shocks $x_{jt} = (\eta^a_{jt}, \eta^\omega_{jt})$.

[32] A nonparametric description of the data suggests that the functional form is reasonable. Figures are available from the authors on request.

[33] Appendix figure E1 shows estimates of the responses to the *transitory* demand shocks derived in Section 4.2. As expected, their impacts are substantially lower than the impact of the permanent shocks, regardless of the sign or magnitude of the shock.

Figure 2: *Shocks and the Net Employment Rate*



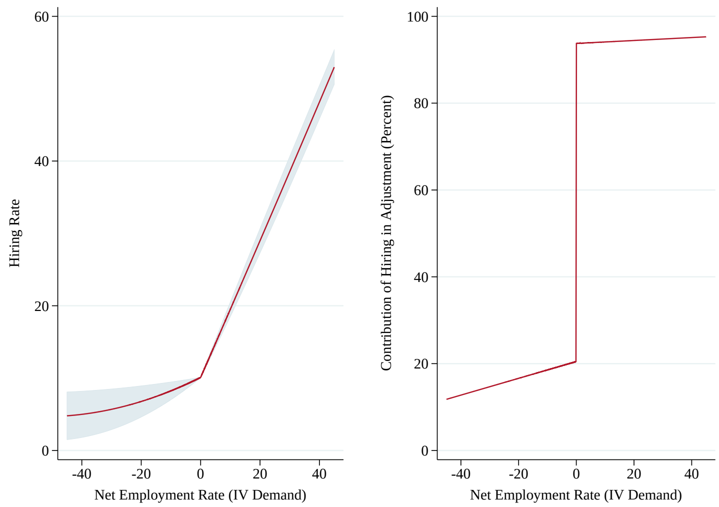
Note: Each line represents the response of the net employment rate in percentage units as a (nonlinear) function of an x standard deviation technology or demand shock. Shaded areas depict 95 percent confidence intervals.

pact on *hiring rate* (the separation response is the exact mirror image) and explicitly calculate the share of adjustments arising from hiring as a function of the sign and magnitude of the shock. For the direct impact of the shocks on hiring and separations, see Appendix E.

The results presented in Figure 3 show evidence of a strongly asymmetric use of the two possible adjustment margins. There is a clear positive and essentially linear relationship between net employment adjustments and hires when employment is growing, but a very modest relationship when employment is shrinking. Trivially, this implies that the separation-response must have the opposite structure. This becomes clear from the right-hand panel in Figure 3, which shows the share of employment adjustment that takes place through hires (versus separations), as a function of demand-induced net employment changes. The share of adjustments through hiring jumps up from 20 to 95 percent when employment adjustments become positive instead of negative. This implies that the share of adjustments through separations jumps down from 80 to 5 percent instead.[34] To complete the picture, Appendix E

[34]In contrast to figure 2 (where zero referred to the absence of an idiosyncratic shock), zero here refers to the state when net employment adjustment is predicted to be zero based on the first stage (i.e., based on the combination of the shock polynomials, year dummies, and firm fixed effects).

Figure 3: *Hiring Rate and Net Employment Changes: IV Results*



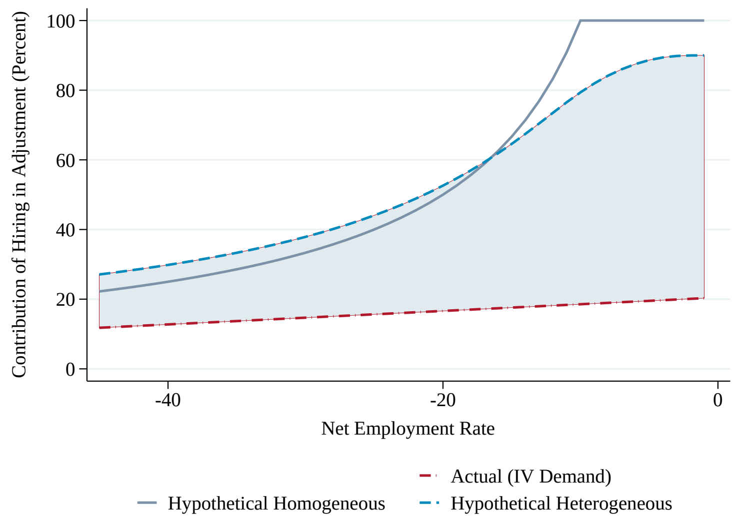
Note: Left-side panel: contemporaneous hiring rate in percentage units as a (nonlinear) function of employment adjustment in percentage units. Employment adjustments are instrumented by demand shocks. The shaded area depicts 95 percent confidence intervals. Right-side panel: implied fraction of employment adjustment achieved through changes in hirings as a function of the size and magnitude of the employment adjustment.

shows the reduced-form impact of the shocks directly on hires and separations, confirming the impression that firms adjust to positive shocks through increased hires and to negative shocks through increased separations.

5.1 Actual and Possible Hiring Responses

Obviously, there are limits to how much a firm *can* reduce its employment by not hiring. We therefore let figure 4 show a set of accounting exercises where we contrast the actual responses from Figure 3 (but focusing on only negative adjustments) with assessments of how much firms *could* have reduced employment without inducing separations. The first assessment scenario, denoted "hypothetical homogeneous," imposes the *average empirical separation rate of firms* with unchanged employment within our data (10 percent) on all firms. In this case, as long as the need for adjustment is 10 percent or less, reduced hires could fully accommodate the necessary employment reduction. If the shock is 20 (30) percent instead, the firm could instead accommodate half (one-third) of the adjustment through reduced hires. The curve shows that firms could have accommodated much larger shocks without induced

Figure 4: *Actual (IV) and Simulated Hiring Responses to Employment Changes*



Note: The figure shows the actual (estimated from data) and hypothetical maximum (simulated) fraction of negative employment adjustments (in percentage units) achieved through changes in hirings. Employment adjustments are instrumented by demand shocks. "Hypothetical homogeneous" assumes that the same fraction of workers always leaves the firm. "Hypothetical heterogeneous" imposes a random individual quit rate on the actual firm size distribution.

separations if the separation rate remained at 10 percent at all times.

But assuming a fixed exit rate of 10 percent is clearly not a valid assumption for small firms, as their number of exits will differ between years for stochastic reasons. We therefore also provide a second benchmark, assuming instead that the *individual* probability of leaving a firm is 10 percent. We randomly allocate quits across all workers in our full sample and then aggregate the data to the firm level to get a firm-level counterfactual distribution of quit rates. Within this distribution, some (primarily small) firms will not experience any quits at all, which means that they cannot accommodate even the smallest employment reduction through reduced hires. Other firms will experience many random separations, allowing them to accommodate large employment reductions through reduced hires. The curve denoted "hypothetical heterogeneous" displays the simulated frontier of adjustments with random individual quits within the data. As is evident, the observed (actual) employment adjustments are far from this benchmark. The actual share of adjustment through reduced hires is much lower than a hypothetical strict reliance on hires would allow for. The shaded area between the heterogeneous hypothetical curve and the actual behaviour of the

firm could be interpreted as a region of flexibility, because it depicts the amount of negative labor adjustments through induced separations (i.e., separations above the random rate) that could have been accomplished through reduced hires instead.

The main take-away from this exercise is that there is substantial scope for firms to rely on a symmetric use of hiring-adjustments (without induced separations) across fairly large positive and negative shocks. But instead, firms choose to let the adjustment margins be an asymmetric function of the sign of the shock, where they primarily vary their separation rates when shocks are negative and instead (almost) only adjust their hiring rates in response to positive shocks.[35] This finding implies that firing costs (broadly defined to include any impediments to separations, for example regulatory restrictions, buyouts, or loss of morale from stayers) do not appear to prevent firms from continuing to hire when they are reducing net employment (see Abowd, Corbel, and Kramarz (1999) for a discussion of the role of firing costs in this context).

6 Conclusions

This paper has analyzed how firms adjust their labor inputs in response to permanent idiosyncratic firm-level shocks to technology and demand. We identify the shocks by imposing a set of long-run restrictions in an SVAR estimated on firm-level data. The restrictions are derived from a stylized model of monopolistically competitive firms. The SVAR is estimated using dynamic panel data methods, allowing us to identify the parameters of the reduced form with considerable precision. To estimate the model, we rely on a very rich data set that merges information about inputs, outputs, and prices of Swedish manufacturing firms with a linked employer-employee data set.

The shocks derived from the SVAR affect output and prices in a theory-consistent way, which lends support to their interpretation as demand and technology disturbances. Firm-level output responds vigorously to technology and demand shocks. In contrast, firm-level prices fall in response to positive technology shocks, but they remain largely independent of product demand innovations.

Our labor adjustment results show that both the nature (as argued by Foster, Haltiwanger, and Syverson (2008)) and time-series properties (as argued by Guiso, Schivardi, and Pistaferri (2005)) of the shocks matter. Permanent demand shocks, which affect output but not relative prices, have a pronounced impact on employment.

[35] In Appendix D we show evidence from heterogeneity analyses related to this process.

In contrast, technology shocks have relatively limited employment effects despite affecting output and relative prices. A similar limited employment response is found for transitory demand shocks, which may explain why we find a larger employment response from demand-side disturbances compared with Pozzi and Schivardi (2016), who do not distinguish between permanent and transitory shocks.[36]

Further results suggest that employment adjustments in response to permanent shifts in the product demand curve are fast and symmetric. By far the largest part of employment adjustment takes place within a year. Almost as much of the employment adjustment is through changes in separation rates as through changes in hiring rates, suggesting that both margins should be considered endogenous at the firm level.

Finally, we provide the first analysis of the asymmetric impact on worker flows (hires versus separations) when employment needs to adjust because of the relevant (i.e., permanent, demand) shocks. The results show that the sign of the shock determines the primary margin of adjustment: firms primarily adjust through separations if shocks are negative and primarily through hires if shocks are positive. The fact that negative shocks are accommodated by increased separations rather than reduced hires implies that the employment adjustments cause excessive worker flows.

The speed of adjustment, symmetry between hires and separations as adjustment margins, and continued recruitment of workers in the face of negative shocks jointly suggest that labor market rigidities play a very limited role in hampering firm-level labor adjustments in the face of permanent idiosyncratic demand shocks. However, the adjustments with respect to transitory shocks are much more muted. Thus, firms accommodate the impact of permanent shocks, but may hoard labor and refrain from hiring when hit by transitory shocks.

The conclusion that the nature of the shocks (technology versus demand) and the time-series properties (permanent versus transitory) of these shocks matter for job and worker reallocation suggests that cross-country comparisons of labor flows need to be careful in accounting for the types of shocks that hit these economies. Building on this notion, our empirical approach also suggests a route forward in trying to understand the forces behind the declining rates of labour adjustments observed, for example, in the United States. Essentially, our empirical approach provides a tool for assessing whether this development is due to the changing nature of the underlying firm-level

[36]Our finding that the impact of technology shocks on employment is small is more similar to Pozzi and Schivardi (2016), which is reasonable since almost all within-firm disturbances in TFPQ are permanent, which makes the distinction between permanent and transitory shocks superfluous.

shocks or the reduced impact of these shocks on labor reallocation. Although this is beyond the scope of this paper, it serves as an example of the type of questions that can be answered by combining data on labor flows with well-identified, firm-level structural shocks.

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Online Appendices for Firm-Level Shocks and Labour Flows by Carlsson, Messina and Nordström Skans

A Data

The firm data sets we use were primarily drawn from Sweden's Industry Statistics Survey (IS) and contain annual information for 1990 to 2002 on inputs and outputs for all Swedish manufacturing plants with 10 employees or more and a sample of smaller plants. Here we focus on firms that have at least 10 employees.

Our measure of real output, Y_{jt}, is the value of total sales taken from the IS deflated by a firm-specific producer price index. The price index uses Paasche-type links constructed from survey information from the Industrins Varuproduktion Survey on reported sales and volume at the goods level collected for all Swedish industrial plants with at least 10 (20) employees for 1990 to 1996 (1997 to 2002) and a sample of smaller plants. In cases of missing information, Statistics Sweden resorts to using price indices at the minimal level of aggregation (starting at the four-digit goods code level up to sectoral producer price indices).

To compute the input index (Δz_{jt}), which is necessary for the computation of the Solow residual (Δa_{jt}) following equation (12), real intermediate inputs (M_{jt}) are measured as the sum of costs for intermediate goods and services (including energy) collected from the IS deflated by a three-digit (SNI92/NACE) producer price index collected by Statistics Sweden. The real capital stock (K_{jt}) is computed using a variation of the perpetual inventory method. In the first step, we calculate the forward recursion

$$K_{jt} = \max((1-\delta)K_{jt-1} + I_{jt}, BookValue_{jt}), \tag{A1}$$

where δ is the sector-specific depreciation rate (two-digit SNI92/NACE) and is computed as an asset share-weighted average between the machinery and buildings depreciation rates (collected from Melander (2009), Table 2); I_{jt} is real net investments in fixed tangible assets (computed using a two-digit SNI92/NACE sector-specific investment deflator collected from Statistics Sweden); and $BookValue_{jt}$ is the book value of fixed tangible assets taken from the Firm Statistics database maintained by Statistics Sweden, deflated using the same deflator as for investment. Moreover, K_{j0} is set to zero if the initial book value is missing in the data. Since, for tax reasons firms want

to keep the book values low, we use the book values as a lower bound of the capital stock. In a second step, we then calculate the backward recursion

$$K_{jt-1} = \frac{K_{jt} - I_{jt}}{(1-\delta)}, \tag{A2}$$

where the ending point of the first recursion, K_{jT}, is used as the starting point for the second backward recursion. This is done to maximize the quality of the capital stock series, given that we lack a perfectly reliable starting point and the time dimension is small. The labour input (i.e., number of employees) is taken from the IS. To compute the revenue shares (used to approximate the cost shares), we also need a measure of the firms' labour cost, which is defined as total labour cost (including payroll taxes) in the IS.

When computing Δa_{jt}, we take an approach akin to the strategy outlined by Basu, Fernald, and Shapiro (2001). First, the C_J (i.e., the output elasticities) are treated as constants. Second, the cost shares are estimated as the time average of the revenue shares for the two-digit industry to which the firm belongs (SNI92/NACE).[37] Third, to calculate the cost shares, we take total costs as approximately equal to total revenues.[38] The cost share of capital is then given by one minus the sum of the shares for all other factors.

Since 1996, Statistics Sweden has imputed the allocation of production across different plants within multi-plant firms. For this reason, we have explored various cuts of the data, focusing on single-plant firms throughout or using multi-plant firms before 1996 but only single-plant firms thereafter. The results are shown in appendix E, table E3, and discussed in the robustness section of the paper.

When computing $\Delta wnulc_{jt}$ and Δwnd_{jt}, we use C_N as the estimate of α and the measure of the firms' labour costs together with the measure of real output and labour input (all discussed in the paper). When computing Δwnd_{jt}, we set σ equal to our estimate of 3.306. Finally, we remove 2 percent of the observations in each tail for each of the distributions of Δa_{jt}, $\Delta wnulc_{jt}$, Δwnd_{jt}, and Δy_{jt}. This has little effect

[37] In the calculation we drop firm-year observations in which the (residual) capital share is below -25 percent of sales. This procedure generates reasonable aggregate cost shares and ensures that the cost shares in all industries are positive.

[38] Using the data underlying Carlsson (2003) and a measure of the user-cost of capital, we find that the time average (1968-1993) for the share of economic profits in aggregate Swedish manufacturing revenues is about -0.001, thus supporting the approximation of cost shares by revenue shares. The result of approximately zero economic profits on average is similar to findings in U.S. data; see, e.g., Basu, Fernald, and Shapiro (2001) for a discussion.

on the estimated coefficients, but it ensures that the structural vector autoregression (SVAR) passes diagnostic tests. We finally require the firm to be observed in spells of at least five years (because we are interested in the within-firm dynamics when estimating the SVAR).

In the end, we construct series for Δa_{jt}, $\Delta wnulc_{jt}$, Δwnd_{jt}, and Δy_{jt} for 7,940 ongoing firms (observed at least during five consecutive years) over 1991-2002. All in all, this amounts to 70,077 firm-year observations. Removing extreme tail events reduces the sample to 6,137 firms and 53,379 firm-year observations (in the specification with output growth as the fourth variable). For these firms, we can compute the structural shocks for 41,105 firm-years (due to lags in the model). Finally, we can match on labour flows from Statistics Sweden's register-based labour market statistics (RAMS) for 6,125 firms and 40,451 firm-year observations. The procedure outlined above implies that changing the fourth variable in the VAR introduces small changes in the sample size.

B The SVAR

B.1 Identification

The log difference of the system outlined in table 1, augmented with the additional transitory variable, has the following vector moving average (VMA) representation (using lowercase letters for logarithms):

$$\Delta \mathbf{x}_t = \mathbf{C}(L)\boldsymbol{\eta}_t, \tag{B1}$$

where $\Delta \mathbf{x}_t = [\Delta a_{jt},\ \Delta wnulc_{jt},\ \Delta wnd_{jt}, \Delta y_{jt}]'$ denotes the first differences of our observed variables and $\boldsymbol{\eta}_t = [\eta^a_{jt}, \eta^f_{jt}, \eta^\omega_{jt}, \eta^y_{jt}]'$ denotes the set of structural shocks. The elements of the four-by-four matrix $\mathbf{C}(L)$ contain polynomials in the lag operator, L, that is, $C_{rc}(L) = \sum_{k=0}^{\infty} c_{rc}(k)L^k$, with coefficients $c_{rc}(k)$ at each lag k. We assume that the shocks ($[\eta^a_{jt}, \eta^f_{jt}, \eta^\omega_{jt}, \eta^y_{jt}]$) are structural innovations and hence mutually orthogonal and serially uncorrelated. Combined with a standard unit variance normalization, we then have $E\boldsymbol{\eta}_t' \boldsymbol{\eta}_t = \mathbf{I}_t$.

Following standard practice, we denote the elements of the matrix of *long-run* multipliers corresponding to (B1) as $C_{rc}(1)(= \sum_{k=0}^{\infty} c_{rc}(k))$. Relying on the model outlined in section 2, we know that the technology shock, η^a_{jt}, is the only shock with

a long-run impact on a_{jt}, so $C_{12}(1) = C_{13}(1) = C_{14}(1) = 0$ in the matrix of long-run multipliers. Similarly, only the technology and factor price shocks have a long-run effect on $wnulc_{jt}$, so $C_{23}(1) = C_{24}(1) = 0$. Finally, since the transitory shock has no long-run effects on wage-neutral demand, it follows that $C_{34}(1) = 0$.

Given these assumptions, we can recover the time series of the firm's structural shocks $\boldsymbol{\eta}_{jt}$. The vector autoregression (VAR) representation of (B1) will be of the form

$$\Delta \mathbf{x}_t = \mathbf{A}(L) L \Delta \mathbf{x}_t + \mathbf{e}_t, \tag{B2}$$

where the elements of the four-by-four matrix $\mathbf{A}(L)$ contain polynomials in the lag operator, L, that is, $A_{rc}(L) = \sum_{k=0}^{\infty} a_{rc}(k) L^k$, and $\mathbf{e}_t$ is a vector of reduced-form errors. Since the errors in the VAR, $\mathbf{e}_t$, are one-step-ahead forecast errors, and comparing (B1) with (B2), we will have that

$$\mathbf{e}_t = \mathbf{c}(0) \boldsymbol{\eta}_t, \tag{B3}$$

where $\mathbf{c}(0)$ is the matrix of $c_{rc}(0)$ coefficients, that is, the coefficients on the contemporaneous structural shocks in the VMA representation. Thus, if the 16 coefficients in $\mathbf{c}(0)$ were known, we could recover $\boldsymbol{\eta}_t$.

In practice, we first use that $E\boldsymbol{\eta}_t \boldsymbol{\eta}_t' = \mathbf{I}_t$ together with an estimate of $\Omega = E\mathbf{e}_t' \mathbf{e}_t$ from (B2) implies 10 restrictions through equation (B3) that can be used to solve for the $\mathbf{c}(0)$ estimate. In addition, we impose the six long-run restrictions. By rewriting equation (B2), we can obtain the VMA form by using equation (B3) in terms of the coefficients in equation (B2) and the $\mathbf{c}(0)$ coefficients as

$$\Delta \mathbf{x}_t = [I - \mathbf{A}(L) L]^{-1} \mathbf{c}(0) \boldsymbol{\eta}_t. \tag{B4}$$

Then, our six long-run restrictions imply an equal number of restrictions on the matrix $[I - \mathbf{A}(L) L]^{-1} \mathbf{c}(0)$, which together with an estimate of (B2) yields six additional restrictions that can be used to solve for the $\mathbf{c}(0)$ estimate. Jointly, these 16 restrictions then allow us to estimate $\hat{\mathbf{c}}(0)$, and using this estimate we can solve for the structural shocks using equation (B3):

$$\hat{\mathbf{c}}(0)^{-1} \hat{\mathbf{e}}_t = \hat{\boldsymbol{\eta}}_t. \tag{B5}$$

When deriving results in terms of elasticities, and to obtain an estimate of the standard deviation of the structural shocks, we use a re-normalized $\hat{\mathbf{c}}(0)$ where each

element is divided by its column diagonal element.

B.2 Estimation and Results

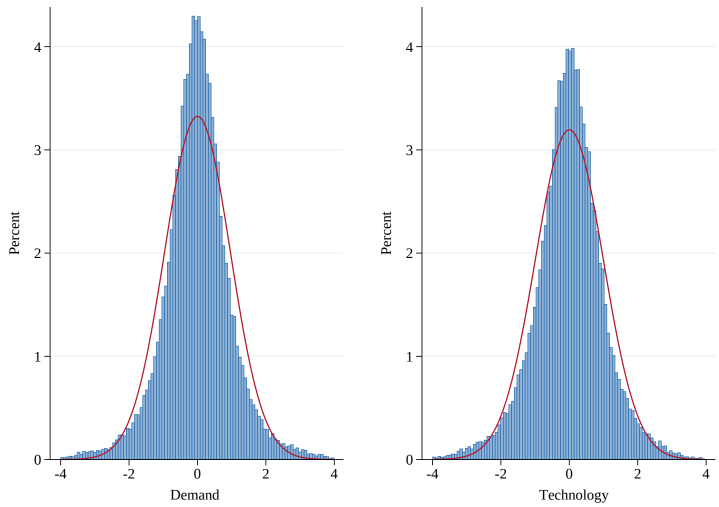
To derive the shocks of interest, we estimate a structural vector autoregression (SVAR) on the three variables defined in table 1: Δa_{jt}, $\Delta wnulc_{jt}$, and Δwnd_{jt}, which are constructed to provide the recursive set of long-run restrictions we need to identify the structural shocks, and a fourth residual variable (which will be output, Δy_{jt}, unless otherwise noted), which will soak up any remaining residual transitory dynamics. In practice, we first estimate four reduced-form equations where Δa_{jt}, $\Delta wnulc_{jt}$, Δwnd_{jt}, and Δy_{jt} are explained by two lags of all four variables (i.e., the VAR). We then invoke the orthogonality and long-run restrictions (including the long-run independence of the core system to the fourth residual shock) to derive the structural shocks and implied impulse responses.

The specification includes firm-specific fixed effects to capture the drift terms of equations (3), (4), and (5) as well as year dummies to capture aggregate shocks shared by different firms in the manufacturing sector, hence allowing us to concentrate on idiosyncratic disturbances. As a robustness check, we also use specifications accounting for sector-specific year dummies.

We use dynamic panel data methods, building on the Arellano and Bond (1991) estimator, which difference out the firm fixed effects, for estimation. The reason is that the asymptotic properties of the estimator rely on the cross-sectional dimension. This is a very useful feature in the current context of a large N (6,137 firms), but short T (12 years) panel, because the identification of structural shocks with long-run restrictions crucially hinges on the quality of the estimated reduced-form coefficients and covariance matrix.

Relying on the Arellano and Bond (1991) autocorrelation test of the differenced residual, two lags in the VAR are enough to remove any autocorrelation in the residuals in all four equations. Here we rely on the two-step Arellano and Bond (1991) difference estimator, using the second to fourth lag levels as instruments. It is worth noting, though, that the parameter estimates are not sensitive to the actual choice of where to cut the instrument set. The results are also insensitive to the inclusion of more lags as instruments. As an additional precaution, we collapse the instrument set to avoid overfitting. That is, we impose the restriction that the relationships in the "first stage" are the same across all time periods (see Roodman (2006) for a discussion).

Figure B1: *Distribution of Demand and Technology Shocks*



Note: Histograms of demand and technology shocks. The distributions are normalized to a have unit standard deviation. Dashed lines depict a normal distribution.

For all specifications, the Hansen test of the overidentifying restrictions cannot reject the null of a correct specification and valid instruments.

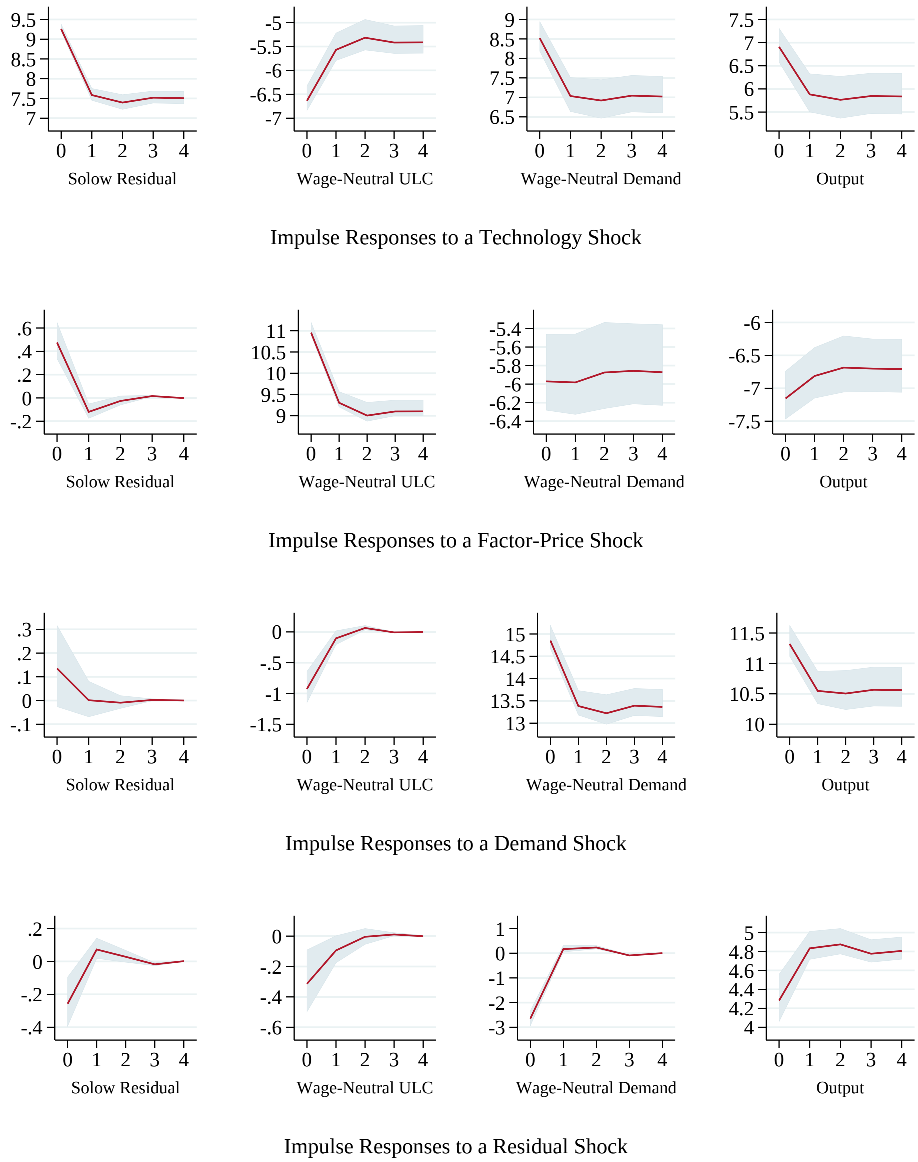
The distributions of the estimated technology and demand shocks are plotted in figure B1.

Figure B2 shows the impulse responses of each of the variables in the baseline VAR in levels to each of the structural shocks. Since the estimated system converges fairly rapidly, we only plot the initial five periods. All impulse responses are precisely estimated, as indicated by the tight (95 percent) confidence bands based on $1,000$ bootstrap replications. The high level of precision is not surprising, given that we estimate the impulse responses on a much larger sample than is common in macroeconomic applications.

We have not been able to find any statistical tests of stationarity that are suitable for a setting with a short but wide panel. However, it should be clear from figure B2 that this issue is of little importance in the current setting. Importantly, the figure is expressed in log-levels, and the flat, non-zero end segments in the responses imply that shocks do have permanent effects on the levels of the series (i.e., the levels are I(1)) and the differenced series are stationary (I(0)).

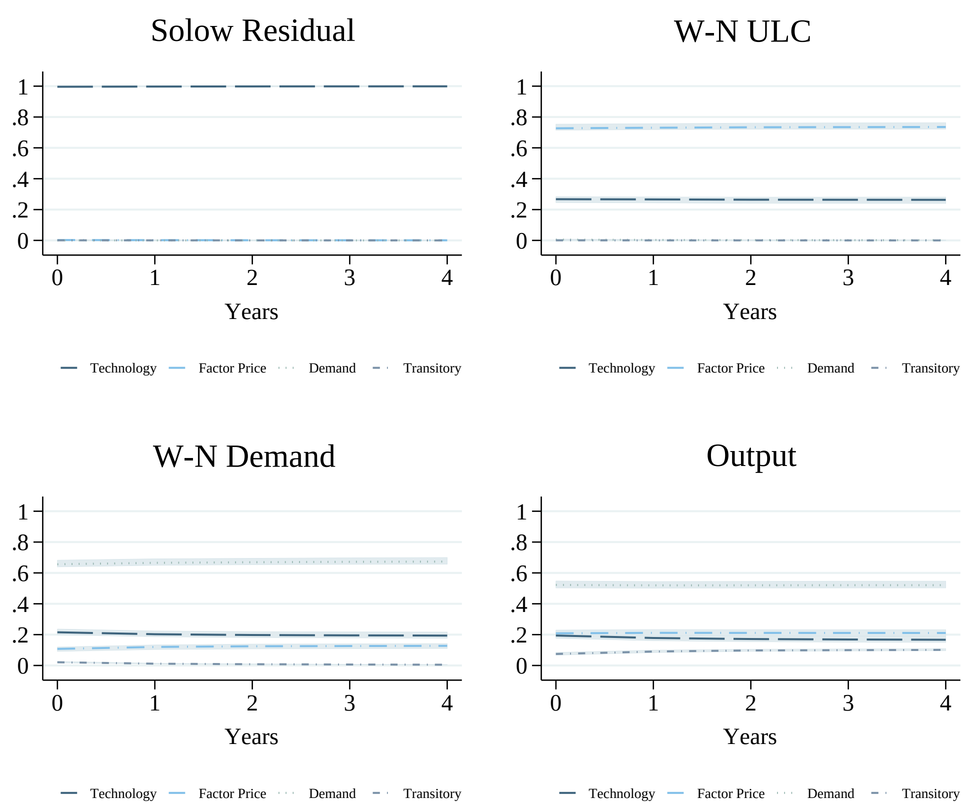
The first row in figure B2 traces out the impulse responses of the Solow residual,

Figure B2: *Impulse Responses*



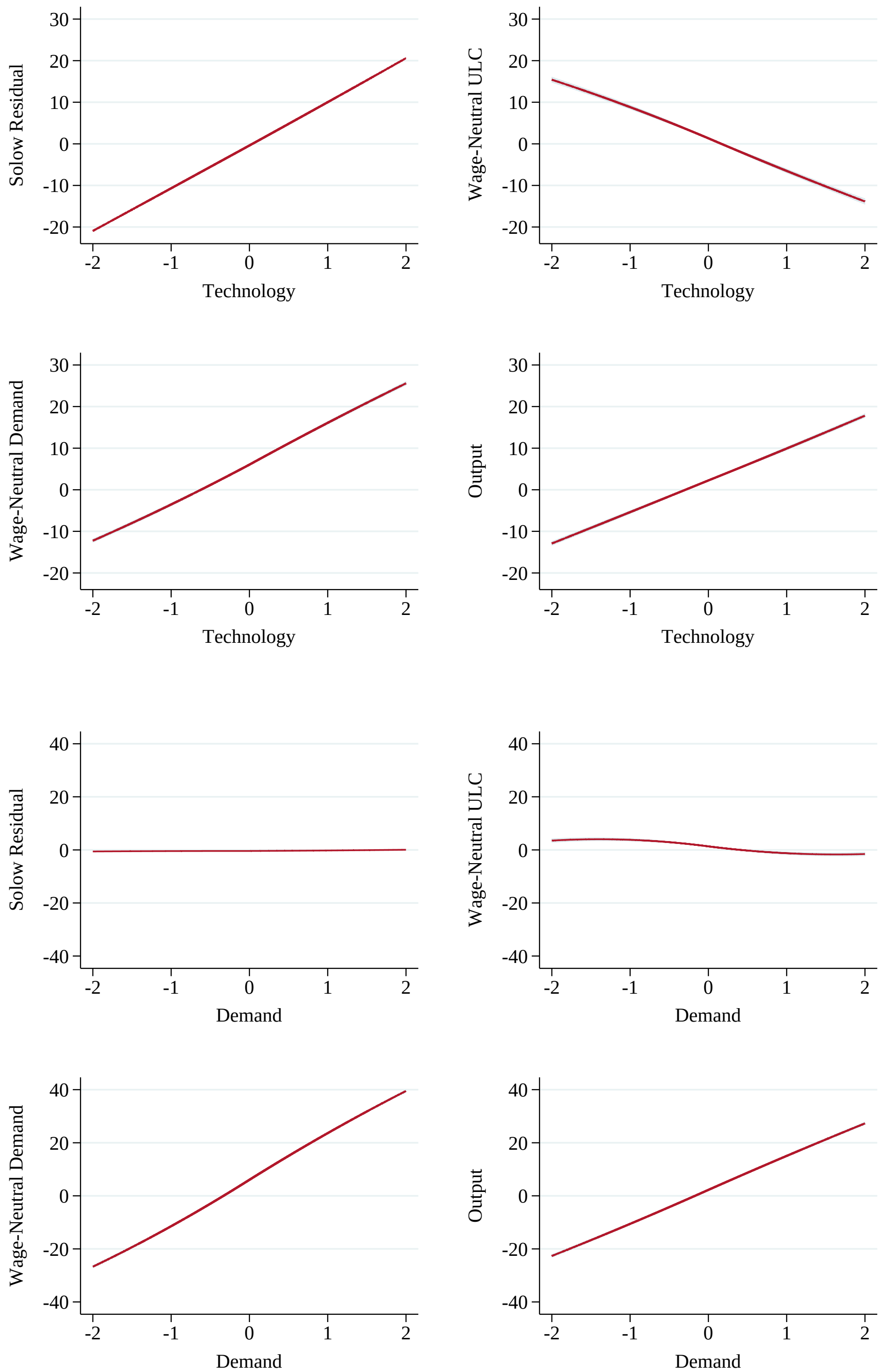
Note: Impulse responses of the Solow residual, wage-neutral unit labour costs (wage-neutral ULC), wage-neutral demand, and output in the baseline VAR to a one standard deviation shock in percentage points. The x-axis denotes years since the shock. Each line depicts the mean of the bootstrap distributions. Shaded areas depict the bootstrapped 95 percent confidence intervals calculated from 1,000 replications.

Figure B3: *Variance Decompositions*



Note: Forecast-error variance decompositions of the VAR in levels. W-N Demand denotes wage-neutral demand. W-N ULC denotes wage-neutral unit labour costs. The left-most panel shows the percentage of the forecast error variance in the Solow residual that can be explained by each structural shock at different horizons measured in years. Each line depicts the mean of the bootstrap distributions. Shaded areas depict the bootstrapped 95 percent confidence intervals calculated from 1,000 replications.

Figure B4: *Nonlinear Responses to a Technology Shock*



Note: Contemporaneous response of variables included in the baseline VAR in percentage units as a (nonlinear) function of an x standard deviation technology or demand shock. Shaded areas depict the 95 percent confidence intervals.

$wnulc$, wnd, and output to a one standard deviation technology shock, η^a_{jt}. Technology shocks have a positive, permanent effect on the Solow residual: a "normal" (i.e., 1 s.d.) shock increases the Solow residual slightly less than 10 percent in the long run. The estimated VAR model does not impose any restrictions on how technology shocks affect $wnulc$ and wnd. However, the results do concur with predictions from expression (7) (in the main text) in the sense that $wnulc$ falls permanently in response to the (permanent) technology shock. Similarly, we find that a permanent technology shock raises wnd, as predicted from expression (8) in the text.

The second row in figure B2 reports the impulse responses to a one standard deviation permanent factor price shock. A "normal" factor price shock increases $wnulc$ and lowers wnd permanently (theoretically working through marginal cost, price setting, and demand). The latter result is, again, an unconstrained result in line with predictions from expression (7). By the same logic, output also falls permanently in response to a factor price shock. The Solow residual is affected in the very short run by factor price shocks but converges to the long-run restriction fairly rapidly.

The impulse responses to a permanent demand shock are shown in the third row in figure B2. In this case, wnd permanently increases in response to a permanent demand shock. In the short run, demand shocks increase the Solow residual and reduce $wnulc$. As expected, a demand shock also has permanently positive effects on output. A "normal" demand shock increases output by about 10 percent in the long run. For completeness, figure B2 also reports the responses to the residual shock in the last row. A "normal" residual shock raises output permanently by slightly more than 5 percent.

We find fairly limited dynamics, in particular in the Solow residual. The main reason for this finding is that the Solow residual is defined in physical gross terms and much of the dynamics in standard measures of Solow residuals appear to be due to the dynamics of idiosyncratic prices (see Carlsson and Nordström-Skans (2012) for direct evidence on relative price dynamics).

Figure B3 presents forecast error variance decompositions for each of the variables in the VAR in levels, decomposing the movements of the three variables. Again, bootstrapped confidence bands are extremely tight. Quantitatively, the Solow residual is solely driven by technology shocks on all horizons. The $wnulc$ is mostly driven by factor price shocks (75 percent of the variation) and partly by technology shocks (25 percent). Demand shocks explain about 65 percent of the movements in wnd,

whereas factor price shocks explain about 20 percent. We also see in figure B3 that there is a role for technology shocks in explaining wage-neutral demand movements, accounting for about 15 percent. For output, we see that about 55 percent of the variation is driven by demand shocks, the rest being explained by factor price shocks (about 20 percent), technology (about 15 percent), and the residual shock (about 10 percent).

Overall though, we find the residual shock to be of little importance. Given that we include time dummies in the VAR, this finding is in line with the results of Franco and Philippon (2007), who find that transitory shocks are not very important at the firm level but account for most of the volatility at the aggregate level, because they are correlated across firms.

A maintained assumption in the analysis is that the baseline VAR is linear in the structural shocks. In figure B4, we plot the predicted contemporaneous responses of the variables included in the VAR as (possibly nonlinear) functions of structural shocks (allowing for a separate second-order polynomial above and below zero). As the graphs show, the results support the maintained linearity assumption.

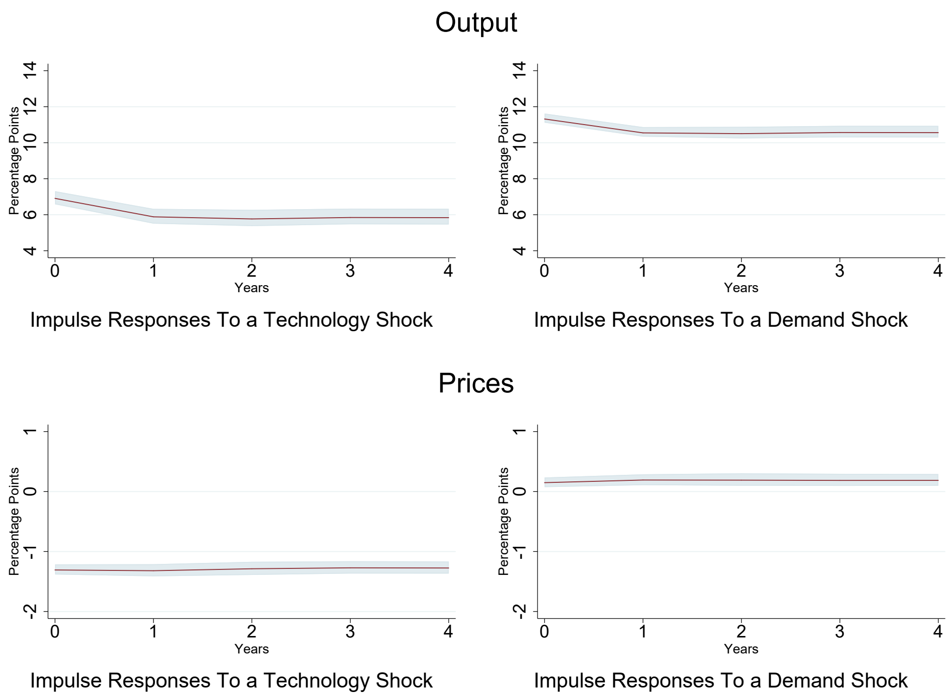
B.3 Validation: The Effects of Shocks on Prices and Output

Because the shocks we are analyzing are idiosyncratic, we cannot use correlations with known aggregate shocks such as oil price or exchange rate movements to cross-validate their interpretation, at least not without strong priors about differences between firms in the sensitivity to these aggregate shocks. A validation exercise comes from relating the permanent shocks to the firm-specific price index and output. If technology shocks only affect the cost of production, we should expect technology shocks to reduce prices, since firms would need to set lower prices to increase their sales along a fixed demand curve. In contrast, demand shocks, defined as shifts in the firm-specific demand curve, allow the firm to sell more at a given price. This suggests that prices should remain unchanged or increase under reasonable pricing strategies.

Hence, economic theory suggests that technology and demand shocks should affect output, whereas prices should fall if the output increase is due to a technology shock (but not if it is due to a demand shock). To assess these general predictions, we reestimate the SVAR and compare the responses of output and prices to the two shocks (using output and prices, in turn, as the fourth variable in the SVAR system).

Figure B5 shows the impulse responses of output and idiosyncratic prices to tech-

Figure B5: *Output and Price Responses*



Note: Impulse responses to a one standard deviation shock expressed in percentage points. The x-axis denotes years since the shock. Lines depict the mean of the bootstrap distributions. Shaded areas depict the bootstrapped 95-percent confidence intervals calculated from 1,000 replications.

nology and demand shocks—indicating that both types of shocks are important for firm-level aggregates. The figure also clearly validates the general predictions discussed above: a one standard deviation technology shock increases output by 6 percent in the long run. In the case of a one standard deviation demand shock, output rises by 10 percent. Moreover, as expected, prices decrease in the case of a technology shock. In contrast, prices *increase* slightly when the demand curve shifts. In our view, the finding that the demand shock permanently changes output without lowering relative prices strongly supports the interpretation of the demand shock as an idiosyncratic shift in the demand curve. These results are not imposed from the construction of our variables: in particular, from a pure measurement standpoint, prices could respond in either direction to structural innovations in technology and demand.

B.4 Non-Constant Returns to Scale

The model can be easily extended to accommodate non-constant returns to scale. Define the overall returns to scale as $\lambda = \alpha + \beta + \gamma$. Notice that under non-constant returns to scale, it is straightforward to show that the measurement of the variables in the system of equations needs to be changed to those of table B1 to retain the recursive form of the long-run impact of the structural shocks. And note that the cost share of a factor will equal the output elasticity divided by the overall returns to scale in optimum, which we use in the empirical implementation provided in table E1.

Table B1: *Summary of the Structural System (Non-Constant Returns)*

Variables:	Measured as:
$Solow:$	$Y_{jt}\left(N_{jt}^{\alpha}K_{jt}^{\beta}M_{jt}^{\gamma}\right)^{-1}$
$WNULC:$	$\left(W_{jt}N_{jt}/Y_{jt}\right)W_{jt}^{-\frac{\alpha}{\lambda}}Y_{jt}^{\left(1-\frac{1}{\lambda}\right)}$
$WND:$	$Y_{jt}^{\left(1+\sigma\left(\frac{1}{\lambda}-1\right)\right)}W_{jt}^{\sigma\frac{\alpha}{\lambda}}$

B.5 Non-Constant Demand Elasticities

In this appendix section, we show that the three identifying long-run restrictions can be reconciled with our observed impulse responses. As shown in the paper, the theoretical long-run predictions for the response of prices, output, and employment to technology and demand shocks under the constant-σ assumption are given by

$$\mathbf{J}^T = \begin{bmatrix} \frac{\partial \ln P_{jt}}{\partial \ln A_{jt}} & \frac{\partial \ln P_{jt}}{\partial \ln \Omega_{jt}} \\ \frac{\partial \ln Y_{jt}}{\partial \ln A_{jt}} & \frac{\partial \ln Y_{jt}}{\partial \ln \Omega_{jt}} \\ \frac{\partial \ln N_{jt}}{\partial \ln A_{jt}} & \frac{\partial \ln N_{jt}}{\partial \ln \Omega_{jt}} \end{bmatrix} = \begin{bmatrix} -1 & 0 \\ \sigma & 1 \\ (\sigma-1) & 1 \end{bmatrix}, \tag{B6}$$

which implies a proportionality factor in the employment responses to technology and demand shocks of $\frac{1}{\sigma-1}$. The corresponding empirical Jacobian, derived from the implied elasticities associated with the impulse responses, presented in figure 1 in the

paper and appendix figure B5, is

$$\mathbf{J}^E = \begin{bmatrix} \underset{(0.008)}{-0.215} & \underset{(0.003)}{0.015} \\ \underset{(0.010)}{0.637} & \underset{(0.007)}{0.711} \\ \underset{(0.021)}{0.050} & \underset{(0.019)}{0.393} \end{bmatrix}, \tag{B7}$$

with robust standard errors presented in parentheses. Thus, one may be tempted to use the Jacobians J^T and J^E to derive an estimate of the structural parameter σ by looking directly at the response of output to the technology shock, or by evaluating the relative impacts of technology and demand shocks. However, as we note in the text, the constant-σ model is deliberately stylized to facilitate a reduced-form identification, and not designed to provide the basis for structural estimation of the parameters of the model. Small departures from this original model that retain the same identification restrictions would lead to very different interpretations of the structural parameters.

One such possible departure from the baseline model assumes, as in section 2.3 of the paper, that the elasticity of demand (and thereby the markup) may be affected by technology and demand shocks, that is,

$$Y_{jt} = \left(\frac{P_{jt}}{P_t}\right)^{-\sigma(A_{jt},\Omega_{jt})} Y_t\Omega_{jt},\ \ \sigma(A_{jt},\Omega_{jt}) > 1 \text{ and } \sigma(\bar{A}_{jt},\bar{\Omega}_{jt}) = \sigma, \tag{B8}$$

where an upper bar denotes an average across firms. The long-run restrictions remain the same as those imposed in the baseline model.[39] However, moving beyond the constant-σ assumption dramatically changes the structural interpretation of the results. Specifically, we now get the following Jacobian

$$\mathbf{J}^{TExtended} = \begin{bmatrix} \left(\frac{-\sigma'_{A_{jt}}}{\sigma(\sigma-1)} - 1\right) & \frac{-\sigma'_{\Omega_{jt}}}{\sigma(\sigma-1)} \\ \left(\frac{\sigma'_{A_{jt}}}{(\sigma-1)} + \sigma\right) & \frac{\sigma'_{\Omega_{jt}}}{(\sigma-1)} + 1 \\ \left(\frac{\sigma'_{A_{jt}}}{(\sigma-1)} + \sigma - 1\right) & \frac{\sigma'_{\Omega_{jt}}}{(\sigma-1)} + 1 \end{bmatrix}, \tag{B9}$$

where $\sigma'_{A_{jt}}$ and $\sigma'_{\Omega_{jt}}$ denote the derivatives of $\sigma(A_{jt},\Omega_{jt})$ with respect to A_{jt} and

[39] Moreover, as discussed in the main text, employment responses to technology and demand shocks are fairly insensitive to large variations in estimated values of σ. Thus, treating σ as a constant or not is not relevant for the main results for all reasonable values of σ.

Ω_{jt}, respectively. We can estimate those derivatives. Imposing $\sigma = 3.306$ (as is the baseline in the paper) and minimizing a loss function (akin to how overidentification is handled in generalized method of moments estimation) in terms of the sum of the squares of the six elements of $\left[\mathbf{J}^{TExtended} - \mathbf{J}^{E}\right]$, weighted by the inverse of the standard deviation of the respective element in J^E, with respect to $\sigma'_{A_{jt}}$ and $\sigma'_{\Omega_{jt}}$, yields $\sigma'_{A_{jt}} = -5.857$ and $\sigma'_{\Omega_{jt}} = -0.763$. The implied reduction in σ from a one standard deviation technology shock is moderate (calculated as the derivative times the standard deviation, that is, $-5.857*0.101 = -0.592$) and even smaller in the case of a demand shock ($-0.763 * 0.162 = -0.124$). Both reductions are tiny compared with the variations of σ (from 1.1 to 10) considered in the main text as robustness exercises.[40] However, computing the elements in $J^{TExtended}$ using $\sigma = 3.306$, $\sigma'_{A_{jt}} = -5.857$, and $\sigma'_{\Omega_{jt}} = -0.763$ gives

$$\begin{bmatrix} -0.232 & 0.100 \\ 0.766 & 0.669 \\ -0.234 & 0.669 \end{bmatrix}, \tag{B10}$$

which is well in line with the estimated responses of prices, output, and employment to the two shocks $\left(\mathbf{J}^{E}\right)$. The main point of this exercise is to show that the identifying assumptions we rely on are consistent with the responses we observe. Obviously, it would be straightforward to decrease the distance for any particular (set of) element(s) within the matrix by giving it a higher relative weight when minimizing the loss function.

[40]Interestingly, the effect on the markup from a technology (demand) shock equals $-1/(1-\sigma)^2$ times the derivative $\sigma'_{A_{jt}}$ ($\sigma'_{\Omega_{jt}}$), which implies that the firm increases the markup slightly in response to a one standard deviation technology shock, 0.111, whereas the markup response to a one standard deviation demand shock is very small (0.023). These results are thus in line with the standard "smoothed-off kinked" demand curve interpretation suggested by Kimball (1995).

C The IV

The IV results presented in figure 3 (in the main text) rely on the following model, where using the indicator function $I_x^+ = I(x_{jt} > 0)$, we have four first stages:

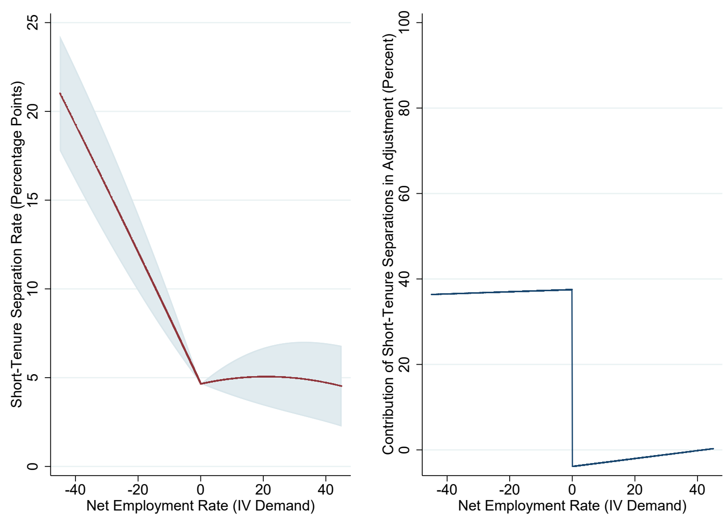
$$
\begin{aligned}
e_{jt} I_e^+ &= g_1^{f1} I_\eta^+ \eta_{jt}^\omega + g_2^{f1} I_\eta^+ (\eta_{jt}^\omega)^2 + g_3^{f1}(1 - I_\eta^+)\eta_{jt}^\omega + g_4^{f1}(1 - I_\eta^+)(\eta_{jt}^\omega)^2 + \rho_t^{f1} + \mu_j^{f1} + \xi_{jt,}^{f1} \\
e_{jt}^2 I_e^+ &= g_1^{f2} I_\eta^+ \eta_{jt}^\omega + g_2^{f2} I_\eta^+ (\eta_{jt}^\omega)^2 + g_3^{f2}(1 - I_\eta^+)\eta_{jt}^\omega + g_4^{f2}(1 - I_\eta^+)(\eta_{jt}^\omega)^2 + \rho_t^{f2} + \mu_j^{f2} + \xi_{jt,}^{f2} \\
e_{jt}(1 - I_e^+) &= g_1^{f3} I_\eta^+ \eta_{jt}^\omega + g_2^{f3} I_\eta^+ (\eta_{jt}^\omega)^2 + g_3^{f3}(1 - I_\eta^+)\eta_{jt}^\omega + g_4^{f3}(1 - I_\eta^+)(\eta_{jt}^\omega)^2 + \rho_t^{f3} + \mu_j^{f3} + \xi_{jt,}^{f3} \\
e_{jt}^2(1 - I_e^+) &= g_1^{f4} I_\eta^+ \eta_{jt}^\omega + g_2^{f4} I_\eta^+ (\eta_{jt}^\omega)^2 + g_3^{f4}(1 - I_\eta^+)\eta_{jt}^\omega + g_4^{f4}(1 - I_\eta^+)(\eta_{jt}^\omega)^2 + \rho_t^{f4} + \mu_j^{f4} + \xi_{jt,}^{f4}
\end{aligned}
$$

and the second stage is

$$
Hiring_{jt} = g_1^S \widehat{e_{jt} I_e^+} + g_2^S \widehat{e_{jt}^2 I_e^+} + g_3^S e_{jt}\widehat{(1 - I_e^+)} + g_4^S e_{jt}^2 \widehat{(1 - I_e^+)} + \rho_t^S + \mu_j^S + \xi_{jt.}^S
$$

D Short-Tenure Workers and Skill Heterogeneity

Figure D1: *Separation Rate of Short-Tenure Workers and Net Employment Changes: IV Results*

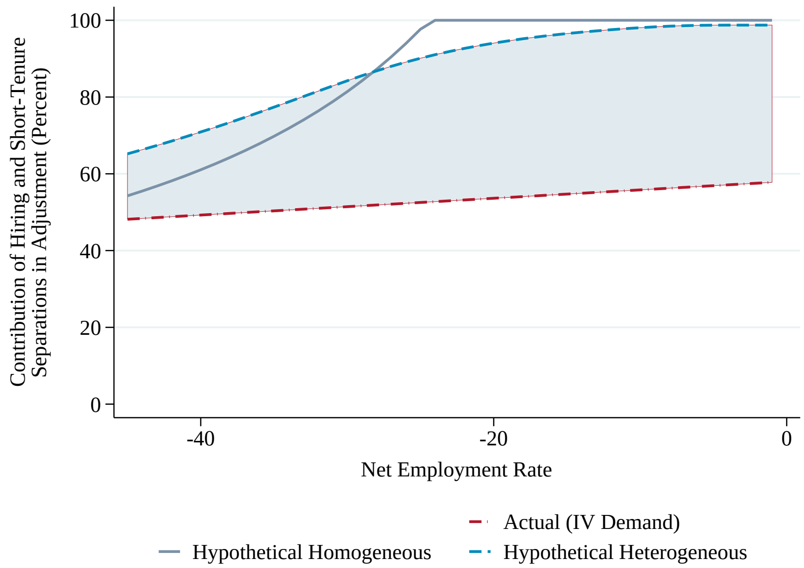


Note: Left-side panel: contemporaneous separation rate of short-tenure workers in percentage units as a (nonlinear) function of employment adjustment in percentage units. Employment adjustments are instrumented by demand shocks. The shaded area depicts the 95 percent confidence interval. Right-side panel: implied fraction of employment adjustment achieved through changes in the separation rate of short-tenure workers as a function of the size and magnitude of the employment adjustment.

One reason for the observed patterns may be that firms adjust by releasing marginal, short-tenure workers who are more likely to be on temporary contracts. Sweden is a country with slightly above-average levels of employment protection (OECD 2014), but the use of temporary contracts is flexible, whereas protection for workers with open-ended contracts is more restrictive.[41] It is thus possible that the labour market responses studied here may hide important heterogeneity across workers, depending on their contract type and tenure with the firm. We do not observe the contract type in the data, but to explore the role played by the (potential) flexibility provided by marginal workers, we have estimated the IV specification using the separation of short-tenure (fewer than three years) workers divided by average employment across the two years. The results, shown in figure D1, suggest that about half of the response

[41] However, this restrictiveness is less pronounced for mass layoffs and mostly concerns layoffs for individual causes.

Figure D2: *Actual (IV) and Simulated Hiring Plus Short-Tenure Separation Responses*

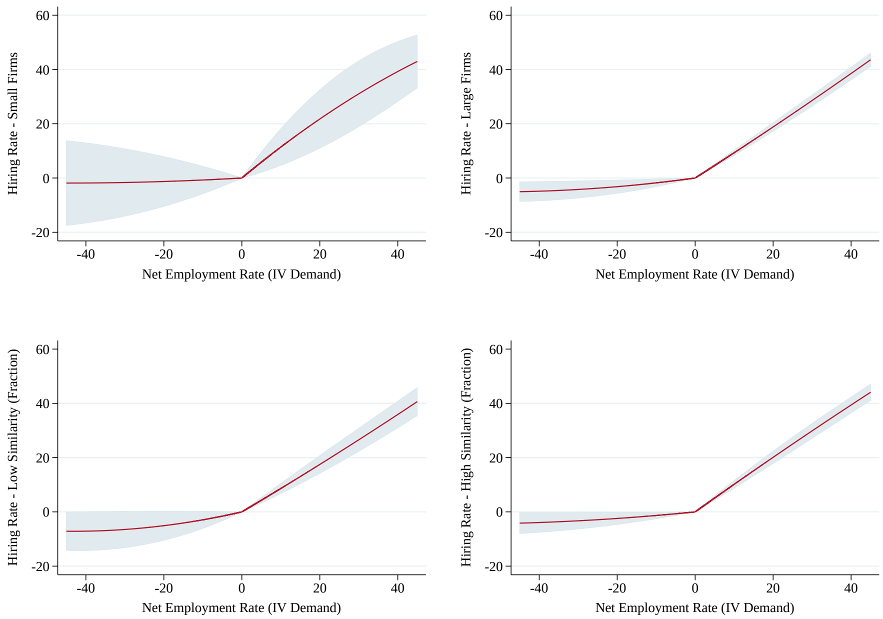


Note: Actual (estimated from data) and hypothetical maximum (simulated) fraction of negative employment adjustments (in percentage units) achieved through changes in hirings and short-tenure separations. Employment adjustments are instrumented by demand shocks. "Hypothetical homogeneous" assumes that the same fraction of workers always leaves the firm and are employed on short tenure (fewer than three years). "Hypothetical heterogeneous" imposes a random individual quit rate and short-tenure rate on the actual firm-size distribution.

to negative shocks comes through reductions in the use of short-tenure workers. We have also repeated the accounting exercise presented in figure 4 (in the main text), but instead contrasting the observed (IV) net employment changes through reduced hires and increased separations of short-tenure workers with the maximum possible adjustment levels through these margins. The results, presented in figure D2, show that firms are far from using the flexibility provided by these two margins. The substantial shaded area in the figure implies that firms rely much more on separations of *long-tenure workers* than would be needed to achieve the same level of net employment reduction.

One obvious reason why firms may choose to shrink through separations rather than through reduced hires is skill heterogeneity within the workforce. If workers who leave for random causes are the "wrong" ones, or if the demand shocks only hit parts of the production process among multi-product firms, *and* if workers are difficult to retrain internally, then the firm may choose to separate some workers and

Figure D3: *Hiring Rate and Net Employment Changes: Firm Size and Worker Heterogeneity, IV Results*

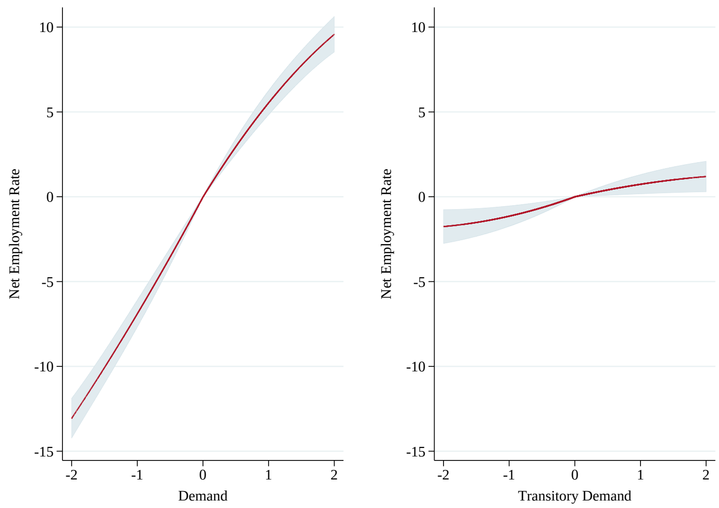


Note: Contemporaneous hiring rates in percentage units as a (nonlinear) function of employment adjustments (in percentage units) in subsamples defined by employee heterogeneity (lower graphs) and firm size (upper graphs). Employment adjustments are instrumented by demand shocks. Low (high) similarity firms are those with a similarity index (calculated as the average share of the workforce with the same three-digit field and two-digit level of education according to ISCED) below (above) the median. Small (large) firms are those with fewer (more) than 20 employees. Shaded areas depict 95 percent confidence intervals.

hire replacement workers for natural exits in other parts of the organization. In a similar vein, smaller firms may have less ability to retrain workers to achieve internal reorganization, relying more heavily on hires and separations. We have explored whether observable differences across firms in skill heterogeneity and size are related to the response margins under the presumption that larger firms and firms with a more homogeneous set of employees should care less about quits and thus rely more on attrition and the separation of short-tenure workers when adjusting their net employment. However, figure D3 does not suggest that the responses differ with firm size and the degree of skill heterogeneity within the firms. However, we acknowledge that the analysis of skill heterogeneity is somewhat crude and leave a deeper assessment as an interesting topic for future work.

E Additional Figures and Tables

Figure E1: *Net Employment and Permanent and Transitory Demand Shocks*

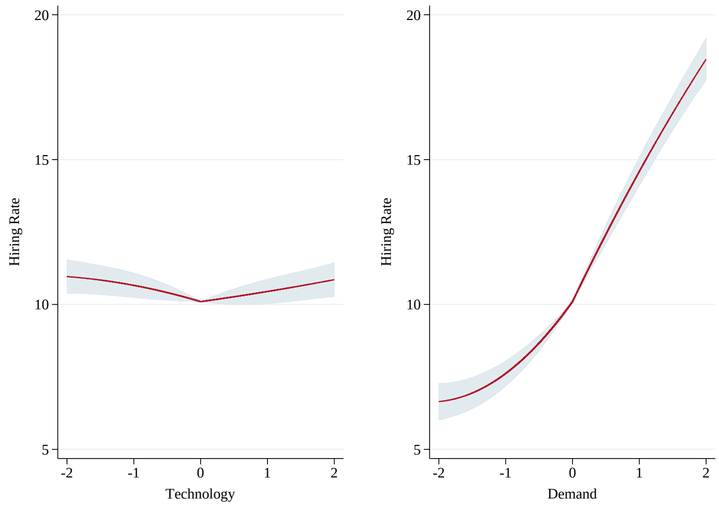


Note: Contemporaneous net employment rate in percentage units as a (nonlinear) function of an x standard deviation of the baseline permanent demand shock and of the transitory demand shock. For details on the derivation of the shocks, see the main text. Shaded areas depict 95 percent confidence intervals.

Demand elasticity. The baseline specification uses an estimated demand elasticity of 3.3. As a robustness check, we have verified that our key results are robust to demand elasticities that vary within what we believe to be the full range of plausible values (from 1.1 to 10); the results in table E2 (columns 2 and 3) show that the estimated coefficients of technology and demand shocks are remarkably stable despite this large interval of measured demand elasticities. Table E2, column 4, shows that the results are unchanged when we allow for industry-specific estimates of the demand elasticity, and column 5 yields similar estimates when we include industry-by-year dummies in the regression to account for different employment trends across sectors. The reason for this robustness is that measured σ only enters our system to handle idiosyncratic wage movements, and these are much smaller than the movements in output against which they are weighted.[42]

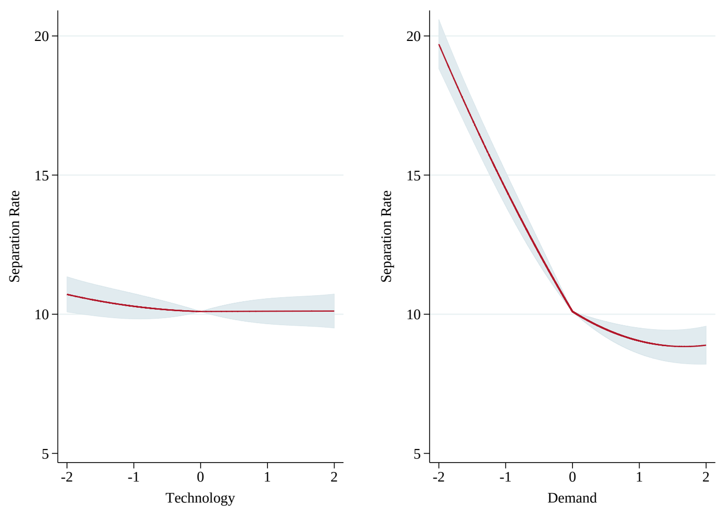
[42] To recap, $\Delta wnd_{jt} = \Delta y_{jt} + \sigma(\alpha * \Delta w_{jt})$. The within-firm standard deviation of Δy_{jt} (0.183) is six times larger than the within-firm standard deviation of $\alpha \Delta w_{jt}$ (0.031) in the data. Furthermore, the two elements are positively correlated (0.10). As a consequence, the within-firm correlation between Δwnd_{jt} measured with $\sigma = 1.1$ and Δwnd_{jt} measured with $\sigma = 10$ is 0.71.

Figure E2: *Shocks and the Hiring Rate*



Note: Each line represents the sum of the average hiring rate among firms that do not adjust employment (10 percent) and the response of the hiring rate in percentage units as a (nonlinear) function of an x standard deviation technology or demand shock. Shaded areas depict 95 percent confidence intervals.

Figure E3: *Shocks and the Separation Rate*



Note: Each line represents the sum of the average separation rate among firms that do not adjust employment (10 percent) and the response of the separation rate in percentage units as a (nonlinear) function of an x standard deviation technology or demand shock. Shaded areas depict 95 percent confidence intervals.

Table E1: *Effects on Log Employment with Different Returns to Scale Assumptions*

	SHORT RUN			LONG RUN		
	(1)	(2)	(3)	(4)	(5)	(6)
	RTS=1	RTS=0.9	RTS = 1.1	RTS=1	RTS=0.9	RTS = 1.1
Technology (η^a)	0.153	0.955**	-0.492**	0.504*	1.378**	-0.244
	(0.159)	(0.161)	(0.149)	(0.214)	(0.211)	(0.232)
Demand (η^ω)	5.986**	6.149**	5.541**	6.357**	6.313**	5.978**
	(0.233)	(0.233)	(0.223)	(0.310)	(0.310)	(0.301)
Observations	40,451	41,132	39,788	34,414	35,031	33,811
Firms	6,125	6,193	6,065	6,116	6,184	6,055
Sd. η^a	10.06	10.04	10.37	10.06	10.04	10.37
Sd. η^ω	16.18	18.74	13.45	16.18	18.74	13.45

Note: Effect of a one standard deviation shock. Robust standard errors are in parentheses. All regressions include firm fixed effects and time dummies. Long-run estimates are obtained by adding the contemporaneous impact and one lag. ** and * denote statistical significance at the 1 and 5 percent levels, respectively.

Sample selection. The data appendix (appendix A) explains that the output allocation across plants within (the relatively few) multi-plant firms after 1996 is imputed in the IS data set. We have therefore redone the analysis for the single-plant firms in the sample (table E3, column 2), as well as for a mixed sample including multi-plant firms until 1996, but not thereafter (table E3, column 3). The results are robust for these alternative samples. The results are also unchanged when the shock distribution is truncated into the Lester range of -2 to $+2$ standard deviations (see table E3, column 4).

Alternative fourth variable in the SVAR. To ensure that the limited dynamics in the employment adjustments we find is not due to the specific way we handle the residual dynamics in the system, we have used sales per worker, output, and employment from our two data sources (RAMS and IS) as alternative fourth variables in the SVAR. Table E4 shows that these variations only have minor impacts on the estimated dynamics and long-run adjustments.[43]

Alternative VAR specifications. Our baseline specification uses unit labour costs as a measure of marginal costs to construct $WNULC$. In an analogous manner, we can use unit material costs, which are equally consistent with the motivating theory.

[43] That the fourth variable plays a negligible role in employment adjustment is also suggested in the variance decomposition shown in appendix B.

Reassuringly, the results are very robust (see table E5, column 2). Columns 3 to 6 in the same table show the results from an alternative two-variable VAR (under various assumptions on σ), based on Foster, Haltiwanger, and Syverson (2008), as discussed in section 2.4. Again, the results are robust.

Table E2: *Effects on Log Employment for Different Values of σ and Sectoral Dynamics*

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline ($\sigma = 3.3$)	$\sigma = 1.1$	$\sigma = 10$	sector-σ	sector-σ	Sectoral Dynamics
			SHORT RUN			
η^a	0.153	0.207	0.259	0.192	0.147	0.126
	(0.159)	(0.158)	(0.152)	(0.161)	(0.162)	(0.162)
η^ω	5.986**	6.591**	4.060**	5.693**	5.520**	5.506**
	(0.233)	(0.240)	(0.198)	(0.221)	(0.222)	(0.225)
Observations	40,451	41,046	39,207	40,214	39,580	39,580
Firms	6,125	6,189	5,998	6,102	5,997	5,997
			LONG RUN			
η^a	0.504*	0.512*	0.643**	0.599**	0.510*	0.490*
	(0.214)	(0.208)	(0.220)	(0.214)	(0.217)	(0.221)
η^ω	6.357**	7.009**	4.267**	5.996**	5.811**	5.737**
	(0.310)	(0.312)	0.291	(0.302)	(0.306)	(0.302)
Observations	34,414	34,612	33,291	34,198	33,667	33,667
Firms	6,116	6,181	5,991	6,094	5,989	5,989
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral σ	No	No	No	Yes	Yes	Yes
Pooled dynamics	Yes	Yes	Yes	Yes	Yes	No
Sector by time FE	No	No	No	No	Yes	Yes
Sd. η^a	10.06	10.16	9.98	10.03	9.94	9.88
Sd. η^ω	16.18	13.87	27.23	17.09	16.98	16.80

Note: Columns 2 and 3 impose large variation in values of σ. Columns 4, 5, and 6 allow for a sectoral σ (for sufficiently large two-digit industries). Column 4 retains joint time dummies. Column 5 lets the time dummies be sector specific. Column 6 reestimates the entire SVAR for each two-digit industry. All estimates are the effect of a one standard deviation shock. Robust standard errors are in parentheses. Long-run estimates are the sum of the contemporaneous impact and one lag. ** and * denote statistical significance at the 1 and 5 percent levels, respectively.

Table E3: *Effects on Log Employment for Sample Variations*

Sample	(1) Baseline	(2) Single Plant Always	(3) Single Plant After 1996	(4) $\leq \pm 2$ Sd. Shocks
		SHORT RUN		
η^a	0.153	0.421**	0.312*	0.040
	(0.159)	(0.158)	(0.151)	(0.164)
η^ω	5.986**	5.500**	6.244**	6.317**
	(0.233)	(0.236)	(0.238)	(0.205)
Observations	40,451	20,877	30,234	36,072
Firms	6,125	3,246	5,259	6,111
		LONG RUN		
η^a	0.504*	0.534*	0.669**	0.336
	(0.214)	(0.233)	(0.215)	(0.234)
η^ω	6.357**	5.715**	6.657**	6.397**
	(0.310)	(0.309)	(0.326)	(0.294)
Observations	34,414	17,638	25,040	30,693
Firms	6,116	3,246	5,250	6,066
sd. η^a	10.06	9.13	9.41	10.06
sd. η^ω	16.18	15.07	14.79	16.18

Note: Column 2 restricts the sample to single-plant firms; column 3 includes a mixed sample with multi-plant firms until 1996, but not thereafter; and column 4 shows results for a trimmed sample where we focus on shocks in the Lester range of $\pm$ 2 standard deviations. The estimates are the effects of a one standard deviation shock. Robust standard errors are in parentheses. All regressions include firm fixed effects and time dummies. Long-run estimates are the sum of the contemporaneous impact and one lag. ** and * denote statistical significance at the 1 and 5 percent levels, respectively.

Table E4: *Effects on Log Employment for Varying the Fourth Variable in the VAR*

	(1)	(2)	(3)	(4)
Fourth variable of VAR:	Output	Sales per worker	Employment (IS)	Employment (RAMS)
		SHORT RUN		
η^a	0.153	0.524**	0.263	0.499**
	(0.159)	(0.154)	(0.143)	(0.061)
η^ω	5.986**	5.840**	5.261**	6.986**
	(0.233)	(0.234)	(0.212)	(0.086)
Observations	41,105	40,284	38,213	37,234
Firms	6,125	6,113	5,879	5,703
		LONG RUN		
η^a	0.504*	0.812**	0.644**	0.643**
	(0.214)	(0.218)	(0.209)	(0.097)
η^ω	6.357**	6.134**	5.477**	7.514**
	(0.310)	(0.317)	(0.266)	(0.121)
Observations	34,414	34,260	32,407	31,531
Firms	6,116	6,102	5,871	5,703
Sd. η^a	10.06	9.980	9.971	9.964
Sd. η^ω	16.18	16.39	15.35	15.13

Note: Column 2 derives shocks from a VAR in which the fourth variable is sales per worker; in column 3, the fourth variable is annual employment measured in the IS data set; in column 4, the fourth variable is end-of-the-year employment measured from the RAMS data set. Sample sizes differ across columns due to data trimming and missing observations in the fourth variable. All estimates are the effect of a one standard deviation shock. Robust standard errors are in parentheses. All regressions include time dummies and firm fixed effects. Long-run estimates are the sum of the contemporaneous impact and one lag. ** and * denote statistical significance at the 1 and 5 percent levels, respectively.

Table E5: *Effects on Log Employment for Alternative VAR Specifications*

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Unit mat. cost	Two var. $\sigma = 3.3$	Two var. $\sigma = 1.1$	Two var. $\sigma = 10$	Two var. sectoral σ
			SHORT RUN			
η^a	0.153	0.183	0.398*	0.261	0.666**	0.427*
	(0.159)	(0.162)	(0.167)	(0.163)	(0.191)	(0.169)
η^ω	5.986**	5.590**	4.331**	4.996**	3.040**	4.314**
	(0.233)	(0.236)	(0.224)	(0.215)	(0.219)	(0.223)
Observations	40,451	40,652	42,280	42,584	40,902	42,175
Firms	6,125	6,154	6,354	6,334	6,343	6,374
			LONG RUN			
η^a	0.504*	0.478*	0.677**	0.431*	0.768**	0.546*
	(0.214)	(0.208)	(0.224)	(0.215)	(0.259)	(0.226)
η^ω	6.357**	5.888**	4.589**	5.612**	3.062**	4.695**
	(0.310)	(0.292)	(0.279)	(0.287)	(0.277)	(0.280)
Observations	34,414	34,594	36,035	36,353	34,689	35,913
Firms	6,116	6,148	6,344	6,326	6,332	6,364
Sd. η^a	10.06	9.93	10.25	10.42	10.04	10.23
Sd. η^ω	16.18	16.67	22.86	17.15	44.06	22.64

Note: Column 2 derives shocks from a VAR replacing unit labour cost with unit materials cost in the expression for WNULC in the second row of table 1 (in the main text). Columns 3 to 6 derive shocks from a two-variable VAR in the Solow residual and the demand shock derived from equation (2) using different values of σ or sectoral σ-estimates. All estimates are the effect of a one standard deviation shock. Robust standard errors are in parentheses. All regressions include time dummies and firm fixed effects. Long-run estimates are the sum of the contemporaneous impact and one lag. ** and * denote statistical significance at the 1 and 5 percent levels, respectively.

Table E6: *Contemporaneous and Long-Run Effects on Net Employment Growth for Two-Period Specifications*

	(1) One period baseline	(2) Two period without exits	(3) Two period with exits
		SHORT RUN	
η^a	0.115	0.282*	0.203
	(0.119)	(0.138)	(0.169)
η^ω	5.609**	5.060**	5.479**
	(0.173)	(0.181)	(0.217)
Observations	40,451	40,063	40,481
Firms	6,125	6,123	6,125
		LONG RUN	
η^a	0.412*	0.530*	0.478
	(0.163)	(0.254)	(0.316)
η^ω	6.009**	4.428**	5.224**
	(0.228)	(0.308)	(0.386)
Observations	34,414	34,032	34,445
Firms	6,116	6,115	6,125

Note: The dependent variable in column 1 is the change in employment between t and $t-1$ divided by the average employment in the two years. In columns 2 and 3, the dependent variable is defined as the change in employment between $t+1$ and $t-1$ divided by the average employment in the two years. Columns 1 and 2 exclude firms that exit the sample in the calculation of the flows, and column 3 includes them. The reported coefficients are the effect of a one standard deviation shock. Robust standard errors are in parentheses. All regressions include firm fixed effects and time dummies. Long-run estimates are the sum of the contemporaneous impact and one lag. ** and * denote statistical significance at the 1 and 5 percent levels, respectively.