Heterogeneous Passthrough from TFP to Wages*

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Abstract

What is the impact of firms' productivity shocks on workers' labor earnings? In this paper we answer this question using a matched employer-employee data that encompasses the entire population of workers and firms in Denmark. Our dataset allows us to separately study continuing and non-continuing workers and to investigate how the passthrough from firms' shocks to wages varies across narrow population groups while correcting for the selection bias arising from endogenous worker mobility. We find that the elasticity of workers' hourly wages to a change in firm productivity is equal to 0.08. This implies that a change of one standard deviation in firm-level TFP drives a change of $1,100 USD in annual wages for the average worker in Denmark. We find that both persistent and transitory shocks are passed on to workers and that there is marked asymmetry between positive and negative productivity shocks. In fact, the elasticity of hourly wages to a negative productivity shock for stayers is twice that of a positive productivity shock of the same magnitude. This suggests that workers are more exposed to negative than to positive shocks to firms. Importantly, we find that the changes in wages due to variation in firm productivity are quite persistent and do not dissipate even after 5 years after the shock. By looking at the heterogeneity of passthrough across the distribution we provide insights about the mechanisms that could explain the asymmetric passthrough we observe in the data.

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1 Introduction

How do fluctuations in firms' idiosyncratic productivity affect workers' wages? How does this vary over time and across firms and workers of different characteristics? The answers to these questions are important as they can help us to understand how firms differ in their ability to set wages, why workers of similar characteristics receive different salaries across firms, and what is the role of firms' shocks in determining worker income instability. At the core of these answers is the idea that some of the gains (and losses) in productivity experienced by firms are passed on to their workers.

In this paper, we use administrative matched employer-employee panel data covering the entire private sector of Denmark to provide new evidence on the passthrough from firms' idiosyncratic productivity shocks to worker's wages. Our main object of interest is the elasticity of changes in individual hourly wages with respect to firm productivity shocks. The richness of our dataset allows us to address some of the challenges faced by the rent-sharing literature. These challenges are two fold. The first is to identify plausible exogenous fluctuations in firms' productivity. Most papers use value added or sales to proxy firm productivity. Fluctuations in these variables, however, might not reflect exogenous shocks but rather endogenous decisions by the firm. In this paper we instead leverage the rich firm and worker-level information available in our dataset to estimate firm Total Factor Productivity using a dynamic structural model. In particular, we build on the nonparametric estimation approach proposed by Gandhi, Navarro and Rivers (2018)–hereafter GNR–combined with a series of two-way fixed-effect wage regressions (as in Abowd, Kramarz and Margolis (1999), hereafter AKM) to control for differences in labor quality across the firms. Importantly, our estimation approach allows us not only to identify plausibly exogenous variation in firm total factor productivity, but also to identify the sign (positive versus negative) and duration (transitory versus persistent) of these shocks.

The second challenge is to identify which workers are affected by the firm shocks. In general, the literature has focused on workers who remain at the firm after a shock ("stayers"'). This may lead to biased estimates of passthrough if, for example, workers tend to quit their jobs rather than suffer a large wage decline resulting from a negative firm shock. Since we can only estimate within-firm passthrough for workers who stay at the firm (who experienced smaller wage changes), estimated passthrough will be biased towards zero, overstating the degree of insurance provided by the firm. In this paper, we address this (selection) bias in two ways. First, we control for the endogenous separation decision by the worker using an exclusion restriction based on the worker's spousal linkages. In particular, we predict each worker's probability of staying at a firm as a function of their own and their employer's characteristics, as well as their relationship status, the characteristics of their spouse and the spouse's employer (if employed), and shocks to their spouse's employer. The underlying assumption is that worker marital status, spousal characteristics, and shocks to their spouse's firm will affect worker job mobility decisions, but not the elasticity of wages to productivity in their own firm. Second, by following workers across firms, we are also able to directly evaluate how differences in firm productivity impact the wages of those workers who switch firms. To the best of our knowledge this is the first paper to directly address selection bias when evaluating the passthrough from firm shocks to worker wages.[1] Correcting for selection turns out to be very important, especially when studying the passthrough of negative productivity shocks.

As a preliminary illustration of our main results, Figure 1 shows the relation between firm TFP growth and worker wages. To construct this figure, we first partition our firms into 41 equally-sized bins based on their TFP growth – measured as the change in log TFP between periods t and $t-1$–with the corresponding density plotted in the left y-axis.[2] Then, within each bin, we calculate two measures of wage growth: the change in workers' log hourly wages (plotted as dots on the right axis) and the residual change in workers' hourly wages after we have controlled for firm and worker observable characteristics and for selection (plotted as squares on the right axis).[3] Three main aspects of this figure are worth noticing. First, the distribution of firms' TFP growth is quite disperse with a substantial share of firms experiencing changes in productivity of more than 30% in a given year: the 90th-to-10th percentile differential is equal to 0.44, which is almost equally split between the left and the right tails, indicating that in any typical year, a firm in the 90th percentile of the distribution experiences a productivity increase of around 22 percent, whereas a firms in the 10th percentile experiences a decrease in pro-

[1]The selection bias problem is commonly recognized in the passthrough estimation literature. A few papers (e.g. Friedrich, Laun, Meghir and Pisteferri (2019)) have attempted to address the problem using two-step procedures similar to our approach. However, these papers have lacked actual exclusion restrictions in the data (such as our spousal data), instead having to rely purely on functional form assumptions on the first stage.

[2]The left and right-most bins encompass the remaining left and right tails of the distribution, and thus are not the same size as the other bins.

[3]Section 3 explains our TFP estimation and selection correction procedures in detail.

ductivity of the same magnitude. Second, workers' wage growth variation is an order of magnitude smaller than the variation of firm productivity growth. This suggests we can also conclude that firms do insulate their workers from shocks, although not completely. Finally, (raw) hourly wages do vary with firms' productivity, especially if the firm experiences an increase in productivity, but appear to be mostly insulated from negative productivity shocks. In fact, the average wage growth is above zero across the entire TFP growth distribution (all dots are above the zero line plotted on the right y-axis), suggesting that (raw) hourly wages are subject to downward rigidity. Hence, simple inspection would indicate that, although there is some passthrough from productivity to wages, this is small and mostly due to positive shocks to productivity. This conclusion, however, ignores the fact that firms with different TFP growth differ in several dimensions, including labor quality, and more importantly, that those workers who stay in the firm after a negative productivity shock are a selective sample. When we control for the endogenous worker mobility the picture changes substantially. In particular, we find an dramatic increase in the slope of the average wage growth coming from the left tail of the TFP growth distribution. Hence, controlling for selection reveals a substantial increase in the elasticity of worker wages with respect to fluctuations in productivity.

The rest of the paper delves into the details of the relationship between firm productivity shocks and worker wages. Our main empirical analysis comprises a series of worker-level panel regressions that relate the change in individual hourly wages for stayers–i.e. workers who remain employed in the same firm–with different measures of firm productivity shocks. Using these regressions, and consistent with the results shown in Figure 1, we find an elasticity of hourly wages to a change in TFP of 0.08 which is economically and statistically significant. Quantitatively, this means that, on average, an individual who works full time at a firm which experiences an increase in TFP of one standard deviation receives an increase in annual earnings equal to $1,075 US dollars, or around 1.8% of the average Danish annual salary. Considering that in a typical year around a 20 percent of the firms in our sample (which employ around 25% of all the workers in the Denmark) experience a change in productivity of at least one standard deviation away from the mean (the standard deviation of firm TFP growth is equal to 0.23 in our sample), we conclude that fluctuations in firm productivity can have important aggregate implications for workers's wages.

We then study whether negative and positive changes in firms productivity do have a differential impact on workers wages. Standard bargaining models predict that for stayers, a positive productivity shocks should command a higher passthrough than negative one as the latter would move the surplus of the match closer to the point at which the match is destroyed. Hence, in average, bargaining models would predict higher passthrough from positive shocks than from negative shocks. Our results, however, indicate just the opposite. In fact, we find that the elasticity of workers wages to negative productivity growth is almost twice as large as the elasticity to a positive change in productivity.[4] Our calculations indicate that for the average worker, an increase in productivity of one standard deviation generates an increase in annual earnings of $840 US dollars, whereas a negative productivity change of the same magnitude generates a drop in annual earnings of $1,580 US dollars.

Our methodology allows us to examine how workers' earnings respond separately to persistent and transitory shocks to firm productivity. With the exception of few papers (see for instance Howell and Brown (2019)), the broad consensus in the literature is that workers' wages respond to persistent changes in firm productivity but do not react to transitory shocks.[5] Our results are consistent with the existing evidence that persistent shocks to firms have a higher passthrough than transitory shocks; However we do find that both types of shocks are statistically and economically significant. By comparing hourly wage changes at different horizons, we show that persistent shocks to firms' productivity have a permanent impact on worker's hourly wages. In contrast, while transitory shocks to productivity do have a significant immediate impact on wages, this impact dissipates almost completely three years after the shock.

As we discussed earlier, selection plays a major role in shaping the impact of firm shocks to workers' wages. Hence, in order to evaluate the extent of the bias generated by selection we provide a set of results in which we do not control for the endogenous selection of workers. By doing this we reach two results, first, selection biases the passthrough coefficient towards zero for both positive and negative shocks, reducing the overall impact of productivity shocks on wages, and second, that this bias is more important for negative than for positive shocks. In fact, if we where to ignore selection, we would conclude that the wage elasticity to positive shocks is almost twice the elasticity to negative

[4]Optimal contract theory also provides insights about the transmission of idiosyncratic productivity shocks to workers' wages. For instance, models with firm commitment as in Harris and Holmstrom (1982) would predict that positive shocks are passed to the wages of stayers while negative shocks are not. Models with imperfect monitoring instead (Lamadon, 2016), predict positive passthrough of both, positive and negative shocks, but this passthrough is symmetric.

[5]See Card, Cardoso, Heining and Kline (2018); Guiso and Pistaferri (2020) for recents reviews of the literature.

shocks, which is the opposite to what we find in our baseline selection-corrected results.

The richness of our dataset allows us to study several degrees of heterogeneity, which help us shed light on different channels that might explain why labor earning risk might be linked to changes in firms' idiosyncratic productivity. Overall, we find that passthrough varies considerably across firms and workers of different types. High wage workers are more exposed to persistent TFP shocks than low wage workers, especially for persistent negative shocks. Older workers benefit more from persistent positive shocks, and suffer less from negative shocks than younger workers. High productivity firms have lower passthrough than low productivity workers, as do firms with more labor market power (defined as higher employment shares within markets of various definition). Passthrough for both persistent negative and positive shocks is also increasing in worker ability. We also find that negative passthrough is hump shaped in tenure, with new workers and long-term workers being less exposed to negative shocks than mid-tenure workers. Transitory shocks display much less heterogeneity in passthrough than persistent shocks across all of these measures. We also find significant passthrough for workers switching between firms. While the elasticity is much smaller than for stayers, the economic impact is twice as large (about $2166 USD on average) since between-firm productivity differences tend to be much larger than within-firm productivity changes. We also find that positive passthrough goes to zero during the Great Recession of 2008-2009 in Denmark.

Our paper relates to several strands of the literature. First and foremost, we contribute to the literature that studies the relationship between firm shocks and worker earnings. Guiso, Pistaferri and Schivardi (2005) analyze the degree of insurance provided by firms using matched employee-employer data from Italy. Their paper, however, does not analyze how firm-level productivity affects employment transitions which might explain a large fraction of the earnings instability observed in the data. Barth, Bryson, Davis and Freeman (2016) and Juhn, McCue, Monti and Pierce (2018) also study the heterogeneity of passthrough from firm's shocks to wages. Barth, Bryson, Davis and Freeman (2016) report that almost three quarters of the dispersion in wage levels is accounted for by differences in TFP levels across firms whereas worker characteristics contribute little. Bagger, Christensen and Mortensen (2014) use Danish data to study the importance of firm level productivity for wage dispersion, the role of rent sharing between workers and firms, and labor force composition within the firm. They document an important role for fixed TFP differences across firms in the determination of earnings level dispersion. These papers, however, do not analyze the role of firm-level

TFP shocks for the dispersion of earnings growth and do not address the endogenous selection of workers. They also typically do not control for changes in hours worked, or for worker ability.[6]

Our paper also relates to the literature that analyzes the extend of downward wage rigidity. The literature on wage rigidity is vast, and several recent papers have studied the presence of wage rigidity using administrative data (see for instance Kurmann and McEntarfer (2019), Grigsby *et al.* (2019), and Elsby and Solon (2019)). Our results suggest that workers experience drops in their (real) hourly wages and that an important fraction of these drops can be traced to negative productivity shocks experienced by firms that employ these workers.

2 Data

Our main source of information is a matched employer-employee administrative dataset from Statistics Denmark covering all years between 1995 and 2010. We obtain worker-level information from the Integrated Database for Labor Market Research which is an annual database containing employment and personal/demographic information for the entire population of Denmark. From this dataset, we obtain several key variables such as annual wages, hourly wages, number of days worked, occupation, labor market status, position within the firm, age, gender, education, and tenure within the firm. Crucially, this dataset identifies the firm in which each worker was employed in the last week of November of each year. Our data also contains spousal links, which means that, for all married workers, we observe the same information for workers' spouses. This information will be crucial when estimating the first-stage of the selection model we use in Section 3.2 to correct for bias in the passthrough regressions. For our baseline results, we consider the change in log average hourly earnings as the main outcome variable at the individual level. In this way, we avoid our results being influenced by changes in the number of hours that individuals work in a year. Importantly, since firms can also respond to shocks by changing the number of hours their employees work, we also study the impact of firms's shocks on the change in log hours and the change in log annual

[6] Several recent papers study the relation between firm's shocks and worker's wages. See for instance Bilal *et al.* (2019), Berger *et al.* (2019), Friedrich *et al.* (2019),Carlsson *et al.* (2015), Garin *et al.* (2018), Guertzgen (2014), Kline *et al.* (2018), Lamadon *et al.* (2017),Rute Cardoso and Portela (2009), and Lagakos and Ordonez (2011). See also Card *et al.* (2018) and Guiso and Pistaferri (2020) for recent surveys.

earnings.

In our baseline sample, we consider full-time workers (defined as individuals that worked more than 35 weeks within a year), who are 15 years and older, whose annualized earnings is above 30,000 DKK (about 4,600 US dollars), and who are not working in the public sector or are self-employed. Our sample selection leaves us with 8.98 million worker-year observations. Table I provides basic summary statistics of our worker-level sample for selected years. Our sample of workers (around 0.5 million workers per year) is 30% female, consists mostly of workers with at least some post-secondary education (65% of the sample), and workers between 25 and 55 years old (˜80%), with an average annual income of $53,103 US dollars in 2005.

We match this individual-level panel to a firm-level panel–the Firm Statistics Register–which contains annual accounting and input use data for the universe of Danish private-sector firms[7]. The key firm-level variables we use are annual revenue, value-added, capital stock, intermediate expenditure, and employment (in full-time equivalents), as well as firm age, location, and industry. This data allows us to construct robust measures of TFP following the methods developed by Levinsohn and Petrin (2003), Ackerberg *et al.* (2015), Gandhi *et al.* (2018), and others. We discard firms with invalid or imputed measures of sales, employment, and other key variables[8]. This is to ensure that we can properly measure firm productivity and mobility of workers across firms. Table II shows few sample statistics for some selected years. Our sample contains around 30 thousands firms per years (for a total of 0.7 million across all years), most of which have been in operation for at least 10 years (67.6%). These old, well established firms represent around 60% of the employment in our sample (showed in parentheses in the middle panel and bottom panels). As in other countries, the employment size distribution is highly skewed, with a small group of firms with 100 or more employees (3% of firms) accounting for a disproportionate share of total employment in the economy (45% of employees).

[7]The register begins with the manufacturing sector in 1995, and gradually adds in the remaining sectors, with universal coverage of the Danish economy from 2001 on.

[8]Our TFP estimation procedure requires data from years $t-1$ and $t-2$ in order to recover productivity in year t. Thus, our final summary stats and estimation sample consists of firms of age 3 and greater, since we do not observe productivity for younger firms.

3 Empirical Strategy

3.1 TFP Estimation

One of the main challenges in studying the passthrough from firms' shocks to workers' wages is to find exogenous sources of variations in firm productivity. The literature has relied on several measures such as variation in value added (Guiso *et al.*, 2005), export demand shocks (Garin *et al.*, 2018), or patent/grant applications (Kline *et al.*, 2018; Howell and Brown, 2019). In this paper we estimate (revenue) TFP shocks using a dynamic structural model of firm production. In particular, we build on the flexible approach proposed by Gandhi *et al.* (2018) with the estimates of fixed effect regressions similar to Abowd *et al.* (1999). In order to conserve space, here we provide a general overview to our estimation procedure. In companion paper (Chan *et al.*, 2019b) we provide further details of this approach and show how controlling for labor quality impacts the shape and dynamics of the firm TFP distribution.

There are several problems we want to address when identifying our firm shock. First, we want to identify exogenous shocks to firm productivity separately from endogenous shifts in inputs. This is important since wages may be correlated with changes in capital stock or employment as well as changes in productivity, and difficult because firms also adjust the capital stock and employment in response to those same exogenous productivity shocks[9]. We are interested in how unanticipated shocks to the firm are passed on to wages, rather than how planned endogenous changes in input mix affect wages. Second, we need to ensure that our estimation method is consistent with the analysis in the rest of the paper. In particular, we need to recover TFP without relying on assumptions that labor markets are perfectly competitive, or that firms are price takers in labor markets, as both directly preclude the possibility of wage passthrough. We also cannot assume that labor is a "predetermined" input like capital, since our empirical analysis hinges on the observation that labor inputs do adjust in response to contemporaneous productivity shocks. Our approach begins with a standard representation of a firm-level gross production function in levels,

$$Y_{jt} \quad = \quad F\left(K_{jt}, L_{jt}, M_{jt}\right) \exp\left(\nu_{jt}\right), \tag{1}$$

[9]This is the transmission bias problem which has been central concern of the TFP estimation literature going back to **?**.

or in logs,

$$y_{jt} \quad = \quad f\left(k_{jt}, \ell_{jt}, m_{jt}\right) + \nu_{j,t}, \tag{2}$$

where ν_{jt} is the Hicks-neutral total factor productivity of firm j in period t. We also assume that ν_{jt} is given by

$$\nu_{jt} \quad = \quad \omega_{jt} + \epsilon_{jt},$$

where ω_{jt} is the persistent component of firm productivity which is assumed to be first-order Markov and given by $\omega_{jt} = \mathbb{E}[\omega_{j,t}|\omega_{jt-1}] + \eta_{j,t}$ and where ϵ_{jt} is an i.i.d. ex-post transitory shock which is uncorrelated with adjustments in inputs. In our estimation we impose standard assumptions on the timing and information sets of the firm's input and production decisions which allow us to separately identify η_{jt} and ϵ_{jt}.[10]

The goal of estimating TFP rather than using value added is to separate ν_{jt} from the adjustments on capital, K_{jt}, labor, L_{jt}, and materials, M_{jt}. As is standard in the literature, we measure Y_{jt}as deflated revenues, K_{jt} as the real deflated value of the capital stock (using the perpetual inventory method) and M_{jt} with the real deflated value of intermediate input expenditures.[11] Several possibilities have been proposed in the literature as a measure of labor input L_{jt}. The most common choice is to use the total number of employees working for firm j in year t or the total number of hours worked by those employees. This is a problem, as cross-sectional differences in the quality or composition of workers across firms will be loaded into ν_{jt}. Similarly, changes

[10] Following GNR, we assume that capital $K_{j,t}$ is a "predetermined" input which is fixed in period $t-1$ and that intermediate materials $M_{j,t}$ is a flexible input chosen every period. We depart from their framework in allowing labor $L_{j,t}$ to be a dynamic input, while GNR assume that labor is predetermined like capital. The timing of the model is such that firms enter period t knowing $(K_{j,t}, L_{j,t-1}, \omega_{j,t-1})$. They then observe $\eta_{j,t}$ and choose $L_{j,t}$(which is allowed to depend arbitrarily on $L_{j,t-1}$through adjustment costs or other factors) and $M_{j,t}$ (which does not depend on $M_{j,t-1}$). After input decisions are set, the firm observes $\epsilon_{j,t}$. We assume that firms can adjust wages in response to both shocks, but that firms are price takers in output markets and the market for intermediate materials.

[11] Using revenues as our measure of output implies that our measure of TFP is "revenue"' TFP rather than "quantity" TFP and thus contains both variation in production efficiency, as well as potential variation in demand. We do not see this as a problem in our context, as we are agnostic regarding the source of the firm shock, as long as it is exogenous to input variation. We allow firms to adjust wages in response to shocks to both efficiency and demand, as both of these represent measures of firm-level risk which may be passed on to workers. We choose to estimate revenue TFP since it allows us to include firms from the service sector which make up the bulk of Danish employment and economic activity.

in the quality of a particular firm's workforce over time, possibly driven by productivity shocks, will also be interpreted as changes in $\nu_{j,t}$. For example, if a firm replaces a full-time janitor with a full-time engineer, their output will likely go up, while the number of hours or employees will remain fixed. This introduces significant bias into any estimates of firm productivity. A second possibility is to use the total wage bill of the firm. In this case, a firm that uses more engineers than janitors will have a larger wage bill, potentially controlling for the difference in ability of these types of workers. There are two main problems arise with this approach. First, there is substantial evidence that firms play a substantial role in the determination of wages and that workers with similar characteristics perceive different wages in different firms.[12] Second, by using the wage bill as a measure of labor quality, we are implicitly assuming that labor markets are perfectly competitive, and in such case we should not expect to see any passthrough from idiosyncratic shocks to workers wages as these would depend only on aggregate conditions.

In this paper we follow a different approach and we use a modification of the additive worker and firm fixed effect model proposed by AKM. In particular, we assume that the log of hourly wages of individual i working in firm j in period t is given by

$$w_{ijt} = \underbrace{\alpha_i + \Gamma' X_{it}}_{\text{Ability Units}} \quad + \quad \underbrace{\psi_{jt} + \xi_{ijt}}_{\text{Per-unit Ability Price}} \quad , \tag{3}$$

where α_i is an individual fixed effect, $X_{i,t}$ is a set of worker observables, ψ_{jt} is a firm-time fixed effect, and ξ_{ijt} is a residual that captures all the different forces that can affect workers' wages but are unrelated to individual or firms characteristics, fixed effects.[13] In this way we are able to separately identify the part of hourly wages that is due to the characteristics of the worker–per worker ability units–from the component of hourly wages that is due to differences across firms–the time-varying per-unit ability price. Furthermore, to estimate this model, we do not need to impose any restriction in the labor market structure that generated the distribution of wages we observe across firms.

[12]For instance, several papers using the AKM approach find that around 20% of the dispersion of workers wages is accounted for by fixed differences across firms. See for instance Barth *et al.* (2016); Song *et al.* (2019); Engbom and Moser (2018).

[13]A further assumption, similar to that in AKM, is that labor mobility cannot be correlated with ξ_{ijt}. However, this assumption is weaker than the AKM assumption, as we do allow workers to switch firms in response to shifts in ψ_{jt},thereby allowing passthrough from firm productivity to play a role in worker mobility decisions.

Notice also we not assumed that the role of the firm on workers' wages is fixed, but rather is time-varying (the time subscript in ψ_{jt}). Although this imposes additional restriction on the construction of our connected set, it a necessary assumption: assuming a time-invariant firm component in the wage equation implicitly assumes that workers wages cannot vary with changes in the productivity of firm j.

We then estimate the model in equation (3) on our sample of Danish workers in a manner similar to the implementation of Card *et al.* (2013) over the entire sample period[14]. Similarly to the results in other studies, we find that around 38% of the variance of log hourly wages is accounted for by individuals' unobserved heterogeneity, 4% is accounted for by worker observables, and another 15% is accounted for by firm characteristics, while the rest is accounted for residual variation.

Finally, using our estimates we define the *ability-adjusted labor input* as

$$A_{jt} = \sum_{i \in J_t} \exp\left(\hat{\alpha}_i + \hat{\Gamma} X_{it}\right) H_{ijt},$$

where J is the set of workers in firm j in period t and H_{ijt} is the number of hours worked by individual i in firm j in period t. Then, we use $a_{jt} = log(A_{jt})$ as our measure of the labor input in equation (2), which allows us to identify a measure of total factor productivity, ν_{jt}, that controls for differences in labor quality. Note that the estimation procedure still allows a_{jt} to be correlated with productivity ν_{jt} via η_{jt} and ω_{jt-1} but not ϵ_{jt}. We can also define the *ability-adjusted log hourly wage,* as $\hat{w}_{ijt} = \psi_{jt} + \xi_{ijt}$, which will be the main dependent variable in the regression analysis in Section 4.

3.2 Selection Model

Most papers analyzing the impact of firms shocks on wages have focused on workers that maintain a stable employment relationship with their firm. The decision of a worker to stay in a firm, however, is endogenous, and ignoring it is likely to bias our estimates. For instance, suppose that after a negative shock a firm decides to reduce the wage for some workers in order to reduce costs. In an extreme case, the firm can simply offer a wage of 0, leaving the worker with no other option that to leave the firm or work for free. If those workers who receive a large wage drop choose to leave the firm, then focusing only

[14]Their model includes firm-worker fixed "match" effects, while ours has firm-time fixed "price" effects. The identification strategy for each is similar, though one likely cannot identify both a worker-varying match effect and a time-varying price effect without additional data.

on the workers that stay–and thus did not experience that large wage drop–would bias our estimates of passthrough towards zero, thereby overstating the degree of insurance provided by the firm.

In order to correct for this in our empirical analysis, we consider a simple model that describes the job stayers' selection problem:

$$\begin{aligned} \Delta w_{ijt} &= \mathbb{X}'_{it}\Lambda + \epsilon^1_{ijt} && \text{if } \; u_{ijt} > 0 \\ \Delta \log w_{ijt} &= \text{unobserved} && \text{if } \; u_{ijt} \leq 0 \\ u_{ijt} &= \mathbb{Z}_{ijt}\delta + \epsilon^2_{ijt} && \\ D_{ijt} &= 1 && \text{if } \; u_{ijt} > 0, \\ D_{ijt} &= 0 && \text{if } \; u_{ijt} \leq 0. \end{aligned}$$

In this setup, u_{ijt} denotes the worker's net utility when she chooses to stay at firm j in period t as opposed to switching to a different firm or out of employment; w_{ijt} and $\mathbb{X}_{ijt}$ are stayers' log hourly wage and the observable characteristics which affect workers' wage growth. Z_{jt} are observable factors including $\mathbb{X}_{ijt}$, which affect the workers' utility of staying in their job. When the net utility from staying in the firm is negative, workers switch out, so we are not be able to observe their within-firm wage change and thus passthrough. We denote whether or not we observe the within firm wage change by the indicator variable D_{ijt}.

Our strategy to correct for the selection follows the standard methods developed by Heckman (1979). Specifically, we assume that the joint distribution for the errors is given by:

$$\begin{pmatrix} \epsilon^1_{ijt} \\ \epsilon^2_{ijt} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & 1 \end{pmatrix} \right].$$

Given this assumption, we estimate a first-stage probit regression of the probability that a given worker stays at her firm as a function of Z_{ijt}, obtaining $\hat{\delta}$. Then we calculate the fitted value of the latent variable $\hat{u}_{ijt}$ and compute the inverse Mills ratio $\hat{\lambda}_{ijt}$ as a function of $\hat{u}_{ijt}$. We then include $\hat{\lambda}_{ijt}$ in our subsequent regressions of worker wage changes on firms productivity shocks to obtain a consistent and unbiased (though not asymptotically efficient) estimator of the passthrough from firms shocks to wages.

Our identification strategy then relies on having a reasonable exclusion restriction for the first stage, in that we can include some firm and worker variation which plays a role in the probability that workers will stay or leave their firm, but does not affect the growth rate of workers' wages should they choose to stay at the firm that period. In order to do this, we use the spousal linkage data to create, for each worker, a set of marital status indicators and–for those with working spouses–measures of their spouse employment status and firm shocks. Specifically, we include in Z_{ijt} indicators for marriage status, separation, change of spouse and whether or not the individual's spouse is working if married. This last term is interacted with other spousal information including log wage, change in log wage, firm TFP and log TFP change, age, experience, and whether or not the spouse is a stayer for that period. We exclude spousal working information if the couple is working at the same firm. The assumption for our instruments is that when a worker is getting married/divorced or his/her spouse has an income or employment change, this will affect the worker's decision on whether or not to keep working at the current firm. However, changes in marriage status, spousal employment, or spousal wages should not affect the passthrough to worker's wage growth at his/her current firm conditional on staying.

4 Results

4.1 The Passthrough from Productivity Shocks to Wages

In this section we discuss our main results, which are based on a series of worker-panel regressions that relate the change in workers' hourly wages to their firms' idiosyncratic productivity shocks. More precisely, our baseline specification is

$$\Delta\hat{w}_{ijt} = \alpha + \beta^{\nu}\Delta\nu_{jt} + \Gamma' Z_{jt} + \Lambda' X_{it} + \delta_t + \zeta_{ijt}, \tag{4}$$

where $\hat{w}_{ijt}$ is the ability adjusted log hourly wage of individual i in firm j and $\Delta\nu_{ijt}$ is the change of log-TFP for j between periods t and $t-1$. The matrices Z_{jt} and X_{it} control for firm characteristics (e.g. lagged productivity, firm size, firm age, etc.) and lagged worker characteristics (e.g. gender, age, tenure in the firm, wage level, etc.) respectively, δ_t is a time fixed effect that controls for aggregate fluctuations in the economy, and ζ_{ijt} is the residual. The matrix X_{it} also includes the inverse of the Mills ratio that controls for the selection of workers into the firm. As we shall see, controlling for selection has important implications for the value of β^{ν}, our main parameter of interest, which measures the passthrough from changes in total firm productivity to worker wages.

The results displayed in Table III show there is significant passthrough from firm TFP shocks to hourly wages. Column (1) indicates an elasticity of worker wages to changes in firm productivity of 0.076. Quantitatively, this implies that a worker employed in a firm that experiences a one standard deviation increase in productivity (about 0.23 log points) receives an increase in average hourly wages of 0.018 log points. This change amounts to $1,074 US dollars for the average full time worker in Denmark (see bottom panel of Table III) or about about 1.8% of their annual income.[15] Given that in a typical year around 20 percent of firms in our sample (which employ around 25% of all the workers in the Denmark) experience a change in productivity of at least one standard deviation away from the mean, we conclude that idiosyncratic fluctuations in firm productivity represent an important source of fluctuations in workers' income.

Our productivity estimates also allow us to separately analyze the passthrough of positive and negative changes to wages. We do so by interacting the change, $\Delta\nu_{jt}$, with a dummy which is equal to one if the corresponding change is negative. The results are shown in column (2) of Table III. First, notice the coefficient for a positive change is slightly smaller than the average change displayed in column (1), but still statistically and economically significant. Second, and more importantly, the elasticity of wages to a negative change in productivity–the sum of the two coefficients–is substantially higher and equal to 0.11. This indicates a one standard deviation change in TFP, conditional on this change being negative, generates a decrease in annual wages for the average Danish worker of 1,600 US dollars, which is almost twice the change in wages after a positive productivity shock of the same magnitude.[16]

We then turn to analyzing the impact of transitory and persistent shocks to productivity on wages. These two types of shocks can have a distinct impact on wages, as firms might be more likely to insure workers from variations in productivity that are perceived as transitory–e.g. a decline in sales because of unexpected bad weather–than from variations that are perceived as persistent–e.g. an increase in sales because of the implementation of a new online platform. Following the estimation approach introduced first by Guiso *et al.* (2005), most papers have consistently found that only persistent

[15] To calculate this and other similar values we simply multiply the value of β times the standard deviation of the measure of firms' productivity change times the average annual wage of the workers of the corresponding sample.

[16] Our analysis so far is only based on workers that stay in the same firm during the period in which the firm experience a productivity change (that is, between t and $t-1$). As we show in Section 4.2.1, this asymmetry is even more striking when we also consider workers that switch firms after a productivity decline.

shocks to firms are passed to wages whereas transitory shocks do not have a significant impact (see Card *et al.* (2018) and Guiso and Pistaferri (2020) for recent reviews).[17] Here we reevaluate the role of persistent and transitory shocks to workers wages by including in our baseline specification the measures of the persistent and the transitory components of firms's shocks estimated in Section 3.1. In particular, our specification is given by

$$\Delta \hat{w}_{ijt} = \alpha + \beta^{\eta} \eta_{jt} + \beta^{\epsilon} \epsilon_{jt} + \Gamma' Z_{jt} + \Lambda' X_{it} + \delta_t + \zeta_{ijt}, \quad (5)$$

where β^{η} and β^{ϵ} are the elasticity of wages to persistent and transitory shock to firms' TFP respectively.

Column (3) of Table III shows the results for the average impact on wages. In contrast to most papers in the literature, we find that both transitory and persistent shocks have a significant impact on hourly wages, although wages are more than two times more responsive to persistent than to transitory shocks to firms' productivity. We then separate the impact of transitory and persistent shocks into their positive and negative parts. Similarly to what we find when look at the total change in firms' TFP, we find marked asymmetry. In fact, as column (4) shows, the impact of a negative persistent shocks is twice as large as the impact of a positive persistent shock. In term of annual earnings, a decline in η_{jt} of one standard deviation generates a drop of \$1,500 USD, whereas an increase in η_{jt} of the same magnitude generates an increase in annual earnings of only \$700 US dollars. We find a similar asymmetric pattern for the transitory shock, with negative transitory having a larger overall impact on wages, though the magnitudes are smaller than for persistent shocks.[18] Hence, we conclude that the passthrough from idiosyncratic productivity fluctuations is not only significant but also highly asymmetric, indicating that an important fraction of the changes in average hourly wages are due to changes in firm productivity.

[17] One exception is Howell and Brown (2019) who find that a transitory cash flow shock to the firm significantly impacts workers' wages. The transitory shocks we study, however, differ from theirs in that a transitory cash flow can imply a persistent change in productivity if that leads to innovation or the incorporation of new technologies.

[18] As mentioned earlier, the literature has found almost no role for transitory shocks to firms. Our results differ from the rest of the studies in the subject mainly because of our estimation strategy and not because of particularities of the data we use. In fact, we if we apply the method of Fagereng *et al.* (2017) in our dataset, we find an elasticity of wages of 0.074 and 0.015 to persistent and transitory shocks to firms (both significant at the 1%). Similarly, Fagereng *et al.* (2017) finds elasticities of 0.071 and 0.018 respectively. Guiso *et al.* (2005) finds similar coefficients (0.070 and 0.0049) using Italian data.

The Importance of Selection

The results on this section would be different if we were to ignore the fact that workers endogenously react to contemporaneous changes in productivity. For instance, our estimates would be biased if after a negative productivity shock that reduces wages for some workers they decide to leave for a better job with higher wages. In such case, only those workers who did not receive a (large) drop in wages will stay in the firm, biasing the impact of firm shocks towards zero. To evaluate the extent to this bias, we repeat the previous analysis but without correcting for worker selection (i.e. we exclude the inverse Mills' ratio from our regressions). The results are shown in columns (5) to (8) of Table III.

Overall, we find that selection biases the impact of firms' shocks to hourly wages towards zero. We also find that the bias is more significant for persistent than for transitory shocks. To see this, compare column (3) to column (7), where the elasticity is halved for persistent shocks but remains the same for transitory shocks. This is consistent with the timing of our production function model, which assumes that inputs are fixed prior to observing ϵ_{jt}. The impact of negative shocks is the most affected by selection, especially for persistent shocks: if we were to ignore selection one would conclude that negative shocks, even when they are persistent, have an elasticity of 0.022, six times smaller than the elasticity implied by our baseline corrected estimates. Given the importance of properly controlling for selection, unless stated, all the results that follow include a selection-correction term.

Wage Persistence and Aggregate Shocks

We complement the previous analysis by studying, first, whether shocks to firms translate into persistent changes in workers' wages, and second, how the passthrough from idiosyncratic shocks to wages compares to the passthrough from industry or aggregate shocks.

Do firm shocks generate long lived effects on workers wages? Intuitively, if shocks to firms only translate into a one period increase in workers wages' (even in the shocks to firms are persistent), one should expect a large contemporaneous passthrough (the correlation between a shock in t with a change in workers wages between t and $t-1$), but a much smaller passthrough at longer horizons (for instance, the correlation between a shock in t and a wage change between $t+4$ and $t-1$ must be closer to 0). Thus, to study the persistence of passthrough, we modify our baseline specification in (5) by extending the horizon of the wage change on the left hand side to $t + k$ periods where k can take values between 0 and 4 while keeping constant the period in which we measure firms' productivity shocks and other firm/worker observables. Note that our selection correction procedure changes as well, such that we run separate first-stage regressions for each separate time horizon, where the dependent variable in the first stage is an indicator of whether the worker stayed at the firm for all 1 to 5 periods.

Figure 2 shows the elasticity of workers wages after a persistent or transitory shock at different horizons. In both panels, the x-axis corresponds to the periods over which the growth is calculated and the vertical lines are 95% confidence intervals. The left panel shows that passthrough from persistent TFP shocks not only is significant in the first year, but also persistent after 5 years, with only a small decay in magnitude. In contrast, transitory shocks are, by nature, short lived, but their effects do not disappear immediately after the shock, generating a boost in worker wages even 3 years after the shock. However, by year 4 the effect is basically zero. As we show in the Appendix, there results are quite robust and persist if we separate positive from negative shocks (Figure A.1) or if we restrict our sample to a balanced panel of workers that stay in the same firm for all the five years after the shock (Figure A.2).

We conclude this section by discussing the differential impact of aggregate and industry shocks on workers' wages. Separating their effect is important as there might be general equilibrium effects that confound our passthrough estimates. Consequently, we follow Carlsson *et al.* (2015) and we first orthogonalize our firm-level productivity change by aggregate cyclical variations, and then we calculate the average productivity growth within an industry-year bin. Then, regress wages changes on the residual firm productivity growth–our measure of idiosyncratic productivity change–and the within industry-year average–our measure of industry shocks. As column (1) of Table IV shows, the elasticity of wages to idiosyncratic firm productivity is almost the same as in Table III, indicating that aggregate shocks play little role in our results (or that the elasticity of hourly wages to aggregate productivity shocks is close to 0). Changes in average productivity at the industry-level (denoted by ΔTFP_t^k) have a significant impact on workers' wages, although the passthrough is less than half than the passthrough from idiosyncratic shocks. Furthermore, if we separate positive from negative shocks, we find that only negative industry productivity changes have an impact on workers' wages. The economic impact is small since there is little variation in industry-level productivity relative to aggregate and idiosyncratic variation.

In this section we have shown that idiosyncratic shocks to firms have a significant and persistent impact on workers wages, which depend not only on the nature of the shocks (persistent versus transitory) but also on the sign of the shock (whether this is positive or negative). In the next section we exploit the richness of our dataset to explore several degree of heterogeneity which will help to shed light on the mechanisms that can generate the large asymmetric passthrough we observe in the data.

4.2 Heterogeneous Passthrough

In order to better understand channels that might explain why labor earnings change after a shock to idiosyncratic firm productivity, in this section we study how the passthrough varies across several key characteristics of the population of workers, such as income level, measured ability, age, and tenure within the firm (Section 4.2.1). On the firm side, we separate companies by their productivity level, labor market power, and relative size (Section 4.2.1). The main conclusion of this section is that passthrough is highly heterogeneous and varyies substantially across groups, especially across workers of different characteristics.

4.2.1 Workers

High versus Low Wage Workers

We first ask whether workers of different levels of income are differentially exposed to the shocks of the firms where they work. This is important for at least three reasons. First, low-income individuals typically have low wealth holdings and are more likely to be credit constrained. Then, to the extent that idiosyncratic shocks to firms represent uninsurable income risk for the workers, a higher passthrough for those workers with the least ability to save might have significant welfare implications. Second, variations in passthrough across income levels might help to explain why individuals at the top and bottom of the income distribution seem to face higher income risk that individuals in the middle of the distribution (Guvenen *et al.*, 2015). Third, differences in payoff schemes might imply differential passthrough for workers at different positions within the firms. In particular, it is possible that CEO earnings are more correlated to firms' performance than regular workers. Hence, one would expect that high-income individuals are subject to a higher passthrough.

In order to shed light on these issues, we separate workers in different quintiles of their annual labor earnings and we estimate the effect of persistent and transitory shocks to firm TFP on wages within each of these groups. Figure 3 summarizes our results. The differences in passthrough between low and high wage workers after a persistent shock to the productivity of their firms are substantial (left panel of Figure 3): The elasticity of hourly wages to a persistent shock to firms' TFP for workers fifth quintile of income distribution is more than three times as big as the elasticity of hourly wages for workers in the first quintile of the distribution. Quantitatively, we find that top quintile workers gain six times more annual income than bottom quintile workers (\$1,763 dollars versus \$285 dollars, which represent 1.9% and 0.8% of the within-group average annual income respectively) when both groups experience a one standard deviation persistent positive TFP shock.

As we discussed earlier, the effect of negative persistent shocks on workers' wages is stronger than the effect of positive shocks. This is true for all workers across the income distribution, but especially for workers at the top quintile in annual income: a negative shock to the persistent component of form productivity generates a drop in annual wages of \$400 dollar for individuals at first quintile of the income the distribution (about 1.1% of the annual income within the group), but a decrease of \$3200 for workers at the top quintile (or about 3.4% of the average income in the group). In other words, we find that high wage workers experience higher gain and even higher pain when their firms experience persistent TFP shocks, which is consistent with the idea that worker compensation is more linked to firm performance as workers move up in the income distribution.[19] The quantitative effect of transitory shocks to TFP is considerably smaller than the effect of persistent shocks (right panel of Figure 3). This is in line with our baseline results: persistent shocks have a more prominent effect on workers wages. Furthermore, relative to a persistent shock, the effect of a transitory shock on wages is much less heterogeneous across the income distribution.

Workers' Ability

We then focus on how passthrough from TFP shocks to workers wages vary across different ability levels. Recall that we define workers ability by combining individual fixed effect and their observable characteristics: $\hat{a}_{it} = \exp(\hat{\alpha}_i + X_{it}\hat{\beta})$. This measure of ability encapsulates variations in income across individuals that are independent of firms. Similarly to our analysis of wages, divide workers in quintiles and estimate the

[19]There is also suggestive evidence that high wage workers and top executives can suffer substantial income losses, especially during a deep recession as the past financial crisis (Guvenen *et al.*, 2014) and such risk can have important implication, for instance, for asset prices (Schmidt, 2016).

effect of persistent and transitory shocks to firm TFP on wages within each of these groups, correcting for selection.

The left panel of Figure 5. shows the effects of persistent TFP shocks on wages. The passthrough from positive persistent TFP shocks to wages increases in workers ability levels. The highest ability quintile workers gain \$1,444 (1.7% increase in their average annual income) dollars on average in response to a one standard deviation of persistent TFP shocks, while lowest quintile workers gain only \$335 dollars on average in response to the same shock. The difference in passthrough is even stronger between workers ability quintiles when firms experience negative persistent shocks. The top ability quintile workers lose \$2,149 dollars (2.5% of their average annual income) on average in response to a one standard deviation negative persistent shock while the bottom quintile workers lose \$529 dollars (1.3% of their average annual income) on average. The fourth quintile workers lose slightly less compare to the top quintile workers when we comparing dollar amounts (\$2,132 dollars versus \$2,149), however, the percentage effect is much bigger for the fourth quintile workers (3.5% of annual income versus 2.5%) since workers in this group have considerably lower level of average income than top quintile workers. Finally, similarly to previous results, we find that the passthrough from negative shocks is higher than the passthrough from positive shocks. This is true for workers at every ability quintiles.

We then turn to the impact of transitory shocks, displayed in the right panel of Figure 5. It is immediately clearly from the graph that the elasticity of workers' to transitory shocks is considerably smaller than the elasticity to persistent shocks and that the effect across different ability quintiles is not very different. Workers at the top quintile gain \$403 dollars (0.5% of annual income) when their firm faces a positive one standard deviation transitory shock, while workers at the bottom gain \$201 (0.5% of their annual income) for the same shock. When firms experience a negative one standard deviation shock, workers at the top of the ability distribution lose \$873 dollars (1%) while workers at the bottom lose \$201 dollars (0.5%). The asymmetry between the effects of a positive transitory shock and negative transitory shock is of much smaller magnitude compared to the case when firms encounter persistent shocks.

Overall, workers with high ability have higher passthrough compare to low ability workers. This is true when a firm faces both positive and negative persistent shocks, however, the wage effects from negative TFP shocks are much stronger than positive shocks. This may reflect that workers with higher ability are typically working at higher-level positions within a firm and therefore receive a bigger bonus (compare to low position workers) when firms are doing well and receive larger bonus cuts when firms face negative shocks.

Workers' Age

Workers may be more or less exposed to firms' TFP shocks depending on their age. On the one hand, one might expect that older workers are likely to be more experienced on average or have greater tenure and therefore are potentially more insured by firms than workers who have just entered the firm–which are typically younger. On the other hand, workers with higher tenure might receive a higher increase in income after a positive productivity shock if the firm borrowed from then in the past, of if their compensation is more linked to firm performance as their move up in the firm payment structure. In order to understand whether workers of different ages are more or less subject to differences in passthrough, we separate workers in five age groups: 15 to 29 years old, 30 to 39 years old, 40 to 49 years old, 50 to 59 years old, and 60 years and older. We then estimate the effect of persistent and transitory shocks to firm TFP on wages within each of these groups, correcting for selection as described in section 3.2.

The left panel of 4 shows the effects of persistent TFP shocks on workers' wages across different wage groups, and the right panel shows the effects of the transitory TFP shocks. On the one hand, the response of wages to persistent TFP shocks is weekly increasing in workers' age when the shocks are positive. In other words, older workers get a higher wage increase than younger workers when firms face a positive TFP shock, though the difference is not very large. Workers who are between 50 and 59 years old gain on average \$806 dollars (1.3% increase in their annual earnings) when firms experience a one standard deviation persistent positive TFP shock, while workers who are below 29 years old gain \$554 dollars (1.2% increase in their annual earnings) in response to persistent TFP shock of similar magnitude.

On the other hand, the response of wages to persistent TFP shocks is decreasing in workers' age when the shocks are negative (for all groups except for workers who are 60 years or older). Workers who are between 50 and 59 years old lose \$1,544 dollars on average in response to a one standard deviation negative TFP persistent shock (2.5% decrease in their annual income), whereas workers who are 29 years old or younger loses \$1,628 dollars on average for the same shock (3.4% of their annual income). Considering that young workers typically have lower incomes and do not have much savings, a low positive passthrough and high negative passthrough might have important implications for their welfare. In contrast, the last age group (60 years or older) has much higher passthrough for both positive and negative shocks relative to other age groups. Overall, we find that young workers see higher pain and lower gains while older workers face the opposite, except for workers who are 60 years and older.

The right panel of Figure 4 shows the effects of transitory TFP shock on wages. Generally speaking, the effect of transitory shocks are much smaller and much flatter across age groups than the effects of persistent shocks. The effects for a one standard deviation transitory shock on workers wage changes range from \$67 dollars wage gain (for workers who are 60 or older) to \$251 dollars (workers who are 29 years or younger). The effects of negative shocks are comparatively bigger. One standard deviation of negative transitory shock decrease young workers (15 to 29 years old) annual wage by \$352 dollars on average, and \$570 dollars for older workers (50 to 59 years old).

Workers' Tenure

We have shown that the passthrough differs substantially across age groups. There might be many reasons behind this finding. For instance, it is well known that young workers tend to move across firms much more than older workers (Topel, 1991). Hence, older workers will have also a long tenure within the firm, which might drive differences in passthrough. In order separately to investigate the effect of tenure from the effect of age, in this section we estimate our baseline specification within tenure groups. In particular, we divide workers into five groups: workers with tenure equal to 2 years or less, tenure between 3 and 4 years, between 5 and 7 years, between 8 and 14 years, and above or equal to 15 years. we choose these cutoffs so that our sample of workers is split into roughly same-sized groups.

The left panel of Figure 6 shows the elasticity of wages to a persistent shock for firms' idiosyncratic productivity. We see that the level of passthrough is roughly hump-shaped for both positive and negative TFP shocks. When firms experience a positive one standard deviation shocks, workers of 15 or more years of tenure see an increase of \$823 dollars (1.3% of their income) on average whereas workers with 2 years or less only gain \$436 dollars (0.8% of income). When the shocks are negative, workers with medium tenure (between 5 and 7 years) lose the most with a negative one standard shock generating a decline of \$2,116 dollars on average income (3.4% of income). For transitory shocks (right panel of Figure 6) the heterogeneity in passthrough across workers in different tenure groups is not significant, and the magnitude is relatively small.

Stayers vs. Switchers

So far we have focused on the effect of TFP shocks on stayers, that is, workers that maintain a stable employment relationship with a firm for the two years over which the change in TFP is calculated. This is a natural starting point as changes in wages for continuing workers can be tied more easily to changes in firm productivity and within the firm's insurance. Moreover, this is the group of workers that the literature has analyzed more often, ignoring the effect of firm shocks on the wages of workers that move between firms. In this section, we extend the existing literature to take into account the effect of idiosyncratic, firm and worker-level, productivity changes on the wages of those workers that move across different employers. This is a large group of workers: in any given year around 20% of Danish workers changed employer. Unfortunately, our annual data do not allow us to distinguish between an individual who passed through an unemployment spell prior to joining a different employer or had a direct transition between employers. Therefore, we will put aside issues related to voluntary or involuntary separations and we will treat all workers who make annual employee-to-employee transitions the same.[20]

Similar to the previous section, we run a set of OLS panel regressions in which the dependent variable is the change in real wages for an individual between two consecutive years and the independent variable is the change in the TFP of the firm in which the individual works. Notice that for switchers the interpretation of a positive or negative productivity shock is different than for stayers. For the latter group, it represents a productivity change for the firm in which they work, whereas for switchers it also captures the difference in productivity between two different firms. Hence, a positive TFP change for a switcher means that the individual moved to a firm with higher TFP relative to the firm at which she used to work, and this change is independent of the actual change in productivity experienced by any of the firms. For instance, it is possible that the transition was motivated by a productivity decline in the firm of origin, or an increase in the productivity of the new firm that poached the worker, or both. To capture these effects we include in the regression the shocks to the productivity of both of the firms the individual is transitioning. In particular estimate,

[20] A register complementary to our data contains monthly job spell histories. We are in the process to merge this dataset to our main sample in order to study how firms' productivity shocks impact workers' transition between jobs and across employment status.

$$\Delta \hat{w}_{ijkt} \quad = \quad \alpha + \beta^{\eta} \eta_{jkt} + \beta^{\varepsilon} \varepsilon_{jt} + \mathbb{Z}'_{jt-1} \gamma_1 + \mathbb{Z}'_{kt-1} \gamma_2 + X'_{it-1} \lambda + \delta_t + \zeta_{ijkt},$$

where $\Delta \hat{w}_{ijkt}$ is the change in real log hourly wages of an individual that works in firm j and moved from firm k. Hence, in this case, η_{jkt} is defined as the unexpected TFP change between the old firm and new firm and is given by $\eta_{jkt} = \omega_{jt} - \mathbb{E}[\omega_{kt}|\omega_{kt-1}]$. The matrix $\mathbb{Z}'_{jt-1}\gamma_1$ includes firm j characteristics as well as firm j persistent TFP change in productivity. Similarly, the matrix $\mathbb{Z}'_{kt-1}\gamma_1$ includes firm $k's$ characteristics and its persistent TFP change. As before the main coefficient of interests are β^{η} which reflects the elasticity of a change in wages as a response to a shock in persistent TFP for the individual, and β^{ε} reflects the elasticity of a change in wages as a response to a transitory TFP shock.

Columns (3) and (4) of Table IV shows the results for this analysis. The effect of persistent TFP changes on wages of switchers is much stronger than it is for stayers. Furthermore, the large difference in dollar values that is associated with the shock to persistent TFP is largely due to the differences in the standard deviation of TFP changes for stayers and switchers, as well as their differences in average wages. For example, the elasticity of wage growth to persistent TFP shocks is much bigger for stayers than switchers when they face negative shocks (0.131 versus 0.027), but the average wage loss from a one standard deviation negative TFP shock for stayers is slightly smaller than switchers ($1,495 dollars vs $1,914 dollars, or 2.5% of annual average income vs 3.4% annual average income). Switchers also on average experience much larger wage increase in wages than stayers: one standard deviation of positive TFP increase is associated with $2,099 dollars wage gain for switchers compare to $688 dollars for stayers that experience an increase in productivity of the same magnitude. These results likely reflect that workers often move up or down in the wage ladder when they decide to switch jobs. Lastly, the transitory TFP shock has a small effect on switchers wages, consistent with previous results.

4.2.2 Firms

Firm Productivity

Does passthrough differ for workers employed by firms in different sectors? Do more productive firms pass a larger or smaller fraction of their productivity gains to wages? Does passthrough vary by firms age and size? Does firms market power impact on the level of passthrough? In this section study whether firms of different productivity levels pass shocks differently to their workers. For instance, it is possible that highly productivity firms, which are typically larger and more established, are better equipped to bear demand fluctuations and shield workers from firm-level shocks. Low productivity firms instead might not have as much resources/flexibilities to insure workers. Furthermore, low-productivity firms are usually younger, and therefore more likely to be credit constrained as they strive to grow.

In order asses the differences in passthrough across firms we proceed as we did with workers in the previous section and we separate firms into five quintiles based on firm's TFP. We then run our baseline regression separately within each group. The left panel of Figure 7 shows our results. We find that when firm experience persistent shocks (positive or negative), the passthrough to workers wages roughly decrease as firms productivity increase. For example, workers of firms at the lowest productivity quintile gain \$789 dollars, or 1.5% of income (loses \$1,427 dollars, or 2.8% of income) on average when their firm experience a positive (negative) persistent shock of one standard deviation.

Workers employed in firms at the highest quintile of the TFP distribution see much smaller income changes. On average, workers gain \$251 dollars, or 0.4 percent of income (lose \$537, or 0.8 percent of income) dollars when their firm faces one standard deviation of positive (negative) persistent shock. Similar to the results from the previous sections, the negative passthrough is considerably bigger than positive passthroughs once we take into account selection. Furthermore, the effect from transitory shock is relatively insignificant relative to the effect from persistent shock especially for high productivity firms. The effects on wages for workers working at high productivity firms from a positive or negative transitory shocks is not statistically different from zero. This result is consistent with the intuition that high TFP firms (which are typically larger and potentially have better access to the financial markets) should be more capable to respond to shocks without impacting labor earnings.

Firm Market Power

An increasing number of papers indicate that firm labor market power and concentration might have increased in the United States over the last decades (David *et al.*, 2017; Dorn *et al.*, 2017). Such increase in concentration might have important consequences, for instance, for mark-ups or the share of total output received by workers (Berger *et al.*, 2019; Lamadon *et al.*, 2019; Chan *et al.*, 2019a). Hence, differences in labor market concentration–a measure of labor market power–may also have an impact on firm-level passthrough from TFP shocks to wages. We ask whether firms with the largest share of employment within a local labor market pass a higher or lower share of their productivity shocks to wages. In particular, we define the labor market power of firm j as the employment share of firm j within a year-municipality bin. We then rank all firms in terms of their share of employment within a municipality and divide them into five quintiles and we run a set of passthrough regression within each group

The result in the left panel of Figure 8 shows how persistent shock affects workers' wage growth across different levels of market power. We find that both negative and positive passthrough is decreasing in the share of employment held by the firm within a local labor market. In responding to one standard deviation productivity shocks, workers in firms with larger market power see on average $829 dollars wage decline when the shock is negative and a $335 increase when the shock is positive. These numbers increased significantly for workers working at firms with low market power: Workers of these firms, on average, see a $1,947 dollars wage drop in response to negative shocks, and $900 dollars in response to positive shocks. The results are again similar to previous ones that negative shocks effect is much stronger than positive ones, and persistent shocks are much more prominent than transitory shocks. We find similar results if we define a labor market by year and industry instead of year and municipality.

5 Conclusions

In this paper, we offer new evidence on the effect of changes in firms' productivity on workers' wages. Using high quality employer-employee matched administrative panel data from Denmark we address two important issues which have been under-addressed by the literature so far: the effect of selection and the impact of changes in firm-level productivity for workers that switch between firms. Moreover, we provide a more direct measure of firm' total factor productivity which is plausibly exogenous to wage setting and labor demand, and we explore several degrees of heterogeneity among firms and workers types. To control for selection, we use a novel approach that exploits employment and income information of worker's spouses to estimate the probability that an individual stays in the same firm during a particular year. We find that controlling for selection has a major impact in the passthrough estimates from TFP shocks to wages. To estimate firm productivity shocks, we extend the literature by allowing for imperfect markets and using a two-sided fixed effect approach to control for unobserved variation in labor quality.

In general, we find that the passthrough from firms' TFP shocks to workers' wages is statistically and economically significant: After we have controlled for selection, we find that a worker in a firm that experiences TFP growth of one standard deviation sees her annual earnings increase by \$1,100 which is around 2% of Danish income per capita. Most of this effect is driven by persistent shocks to firms' productivity. Furthermore, there is a substantial asymmetry in the passthrough from positive and negative shocks: the elasticity of worker's hourly wage to a negative shock to firms' idiosyncratic productivity for stayers is almost two times as large as the elasticity to positive shocks. In other words, workers are more exposed to negative than positive shocks to firms' productivity.

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Table I – Summary Statistics for Workers

	2000	2005	2010
Observations	469,922	653,283	625,237
% Women	28.0	30.0	31.0
% High School or less	33.7	29.6	27.4
% Age groups			
Below 25	8.69	6.7	8.1
25-35	30.6	26.7	21.4
36-45	27.03	30.9	31.4
46-55	23.3	22.3	25.4
Above 55	10.3	13.4	14.0
Real Labor Earnings			
Mean	49,513	53,104	54,176
P10	34,544	35,954	35,954
P50	48,533	51,534	52,052
P90	77,653	83,283	87,553

Table I show samples statistics for workers. All monetary values are converted to US dollars of 2010.

Table II – Summary Statistics for Firms

	2000	2005	2010
Observations	29,561	45,180	48,289
% Age groups			
<5	8.9 (6.2)	10.9 (6.3)	11.4 (5.0)
5-10	23.5 (35.7)	44.3 (33.9)	48.5 (34.9)
10+	67.6 (58.2)	44.9 (59.9)	40.1 (60.1)
% Employment			
20	83.0 (24.3)	84.1 (25.5)	87.4 (28.2)
20-100	13.9 (28.1)	13.1 (28.8)	10.4 (26.6)
100-1000	3.0 (36.7)	2.6 (35.2)	2.2 (33.3)
1000+	0.12 (10.8)	0.1 (10.5)	0.11 (11.8)

Table II show samples statistics for firms. All monetary values are converted to US dollars of 2010.

Table III – Passthrough from Firms' TFP shocks to Wages

Dep. Variable	Change of Log Hourly Wages, $\Delta w_{i,j,t}$							
	Selection Corrected				Uncorrected			
Specification:	(1) All	(2) Pos/Neg	(3) All	(4) Pos/Neg	(5) All	(6) Pos/Neg	(7) All	(8) Pos/Neg
$\Delta\nu_{jt}$	.076***	.060***			.046***	.062***		
	(.004)	(.004)				(.004)		
$\Delta\nu_{jt}\mathbb{I}_{\Delta\nu_{jt}<0}$		.053***				-.032***		
		(.005)				(.005)		
η_{jt}			.077***	.061***			.033***	.044***
			(.007)	(.004)			(.004)	(.004)
$\eta_{jt} \times \mathbb{I}_{\eta_{jt}<0}$				.067***				-.022***
				(.007)				(.009)
ϵ_{jt}			.034***	.025***			.034***	.032***
			(.003)	(.005)			(.003)	(.004)
$\epsilon_{jt} \times \mathbb{I}_{\epsilon_{jt}<0}$				.018**				.007
				(.008)				(.009)
$Mills_{it}$	-.219***	-.278***	-0.188***	-.262***				
	(.014)	(0.015)	(.023)	(.013)				
R^2	.78	.78	.79	.79	.78	.78	0.78	0.78
Obs (M)	6.47	6.47	6.47	6.47	6.47	6.47	6.47	6.47
	Monetary Value of a Shock to Firm TFP (US$ 2012)							
$\Delta\nu_{jt}$	1,074.7				654.9			
$\Delta\nu_{jt} > 0$		839.6				873.2		
$\Delta\nu_{jt} < 0$		1,578.5				403.02		
η_{jt}			873.3				386.2	
$\eta_{jt} > 0$				688.6				503.8
$\eta_{jt} < 0$				1,494.5				251.9
ϵ_{jt}			335.8				352.64	
$\epsilon_{jt} < 0$				251.9				319.1
$\epsilon_{jt} > 0$				436.2				386.2

Table III shows a set of OLS panel regressions controlling for firm and worker characteristics. All regressions include firm-level controls (which include, firm age, lagged firm TFP level, firm employment, and total firm ability), worker-level controls (which include, a polynomial in age, lagged worker experience, lagged log wage level, lagged tenure in the firm, gender, and lagged log ability), the inverse of Mills ratio to control for selection, and year fixed effects. $*p < 0.1, **p < 0.05, ***p < 0.01$. Robust standard errors are clustered at the firm-level.

Table IV – Passthrough from Firms and Industry TFP shocks to Wages

Dep. Variable	Change of Log Hourly Wages, $\Delta w_{i,j,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
	Industry and Aggregate Shocks					
Specification:	All	Pos/Neg	Stayers	Switchers	Expansions	Recessions
$\Delta\nu_{jt}$	.076***	.058***				
$\Delta\nu_{jt}\mathbb{I}_{\Delta\nu_{jt}<0}$		.060***				
$\Delta\nu_t^k$	.024***	0.00				
$\Delta\nu_t^k\mathbb{I}_{\Delta\nu_t^k<0}$		.046*				
η_{jt}			.061***	.026***	.056***	.014
$\eta_{jt} \times \mathbb{I}_{\eta_{jt}<0}$			.131***	.025***	.136***	.141***
ϵ_{jt}			.025***	.077***	.025***	.032***
$\epsilon_{jt} \times \mathbb{I}_{\epsilon_{jt}<0}$			.032***	.040***	.046***	.025***
$Mills_{it}$	-.209***	-.275***				
R^2	.78	.78				
Obs (M)	6.47	6.47				
	Monetary Value of a Shock to Firm TFP (US$ 2012)					
$\Delta\nu_{jt}$	1,041.1					
$\Delta\nu_{jt} > 0$		789.2				
$\Delta\nu_{jt} < 0$		1,595.2				
$\Delta\nu_t^k$	67,17					
$\Delta\nu_t^k > 0$		0.0				
$\Delta\nu_t^k < 0$		117.6				
$\eta_{jt} > 0$			688	2,099	638	167
$\eta_{jt} < 0$			1,495	1,914	1,528	1,662
$\epsilon_{jt} < 0$			252	554	252	336
$\epsilon_{jt} > 0$			437	369	453	269

Table IV shows a set of OLS panel regressions controlling for firm and worker characteristics. All regressions include firm-level controls (which include, firm age, lagged firm TFP level, firm employment, and total firm ability), worker-level controls (which include, a polynomial in age, lagged worker experience, lagged log wage level, lagged tenure in the firm, gender, and lagged log ability), the inverse of Mills ratio to control for selection, and year fixed effects. $*p < 0.1, **p < 0.05, ***p < 0.01$. Robust standard errors are clustered at the firm-level.

Figure 1 – Passthrough form Firms' Growth to Workers' Wages

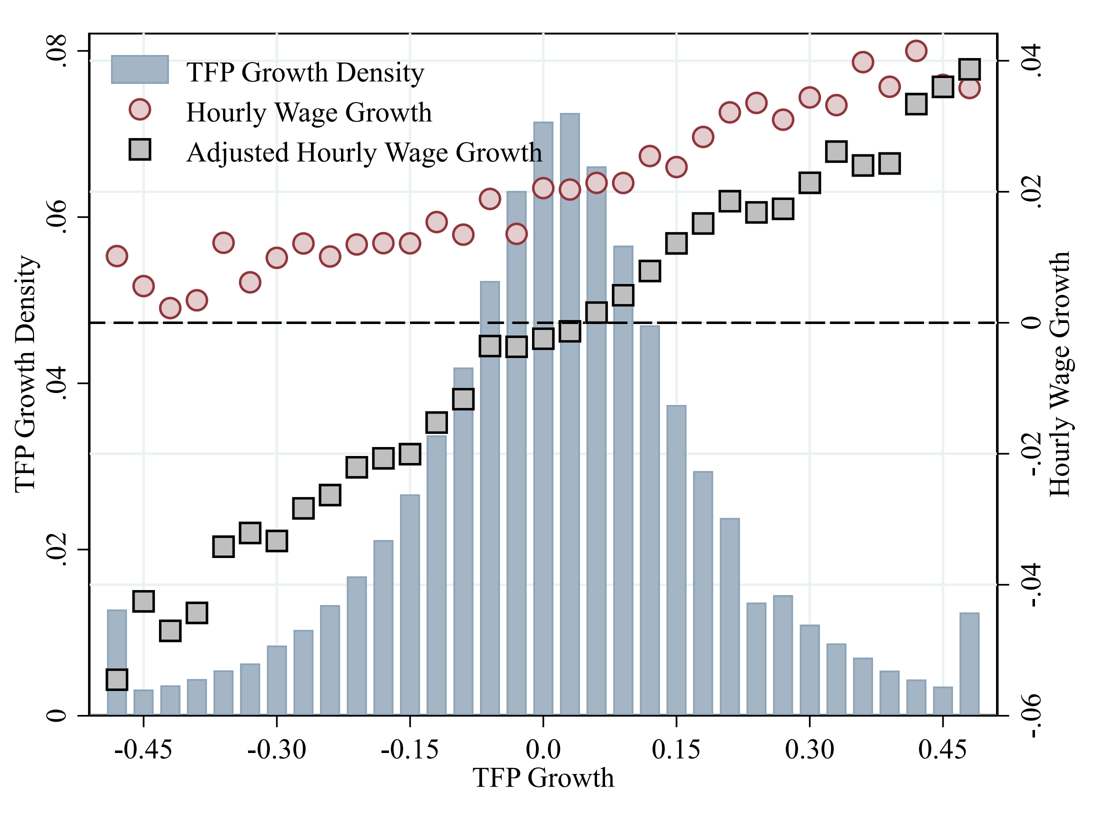
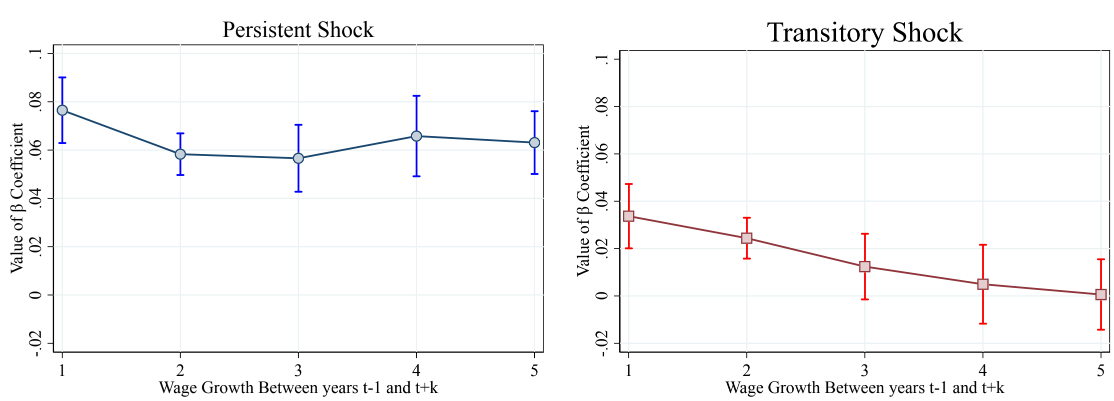


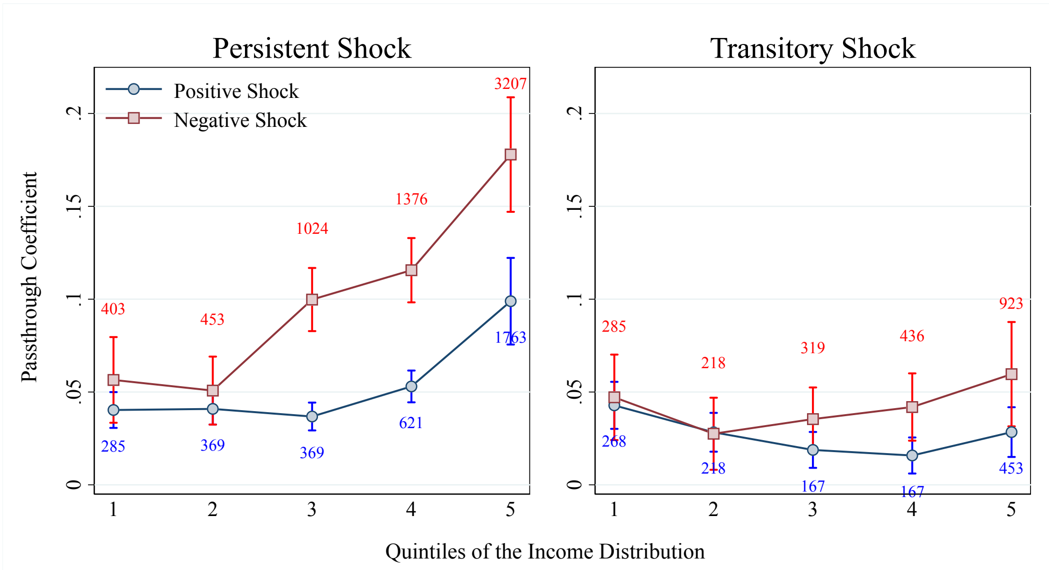
Figure 1 is based on a pooled sample of firms and workers between years 1992 to 2010. The blue bars show the share of firms within different bins of the TFP growth distribution (left y-axis). The red dots show the average hourly wage growth for all workers employed by firms within a bin (right y-axis). The black squares show the average hourly wage growth after controlling for worker characteristics, firms characteristics, and endogenous selection.

Figure 2 – Shocks to Firms Have a Long-Lived Impact



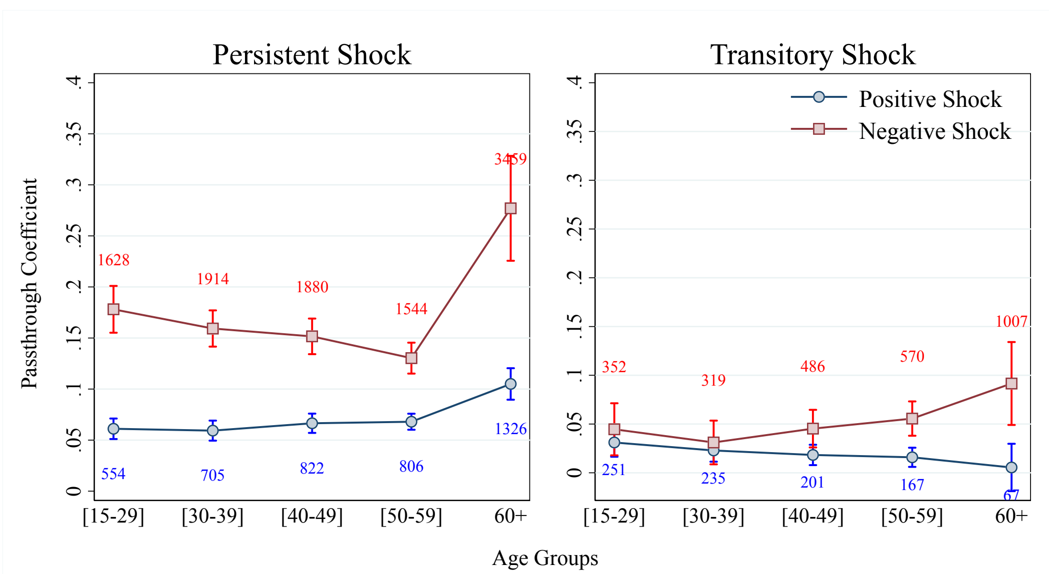
Note: Figure 2 shows the elasticity of hourly wages to a persistent (transitory) shock to firms productivity. In each plot the vertical lines show a 1% confidence interval.

Figure 3 – Passthrough by Wage Quintiles



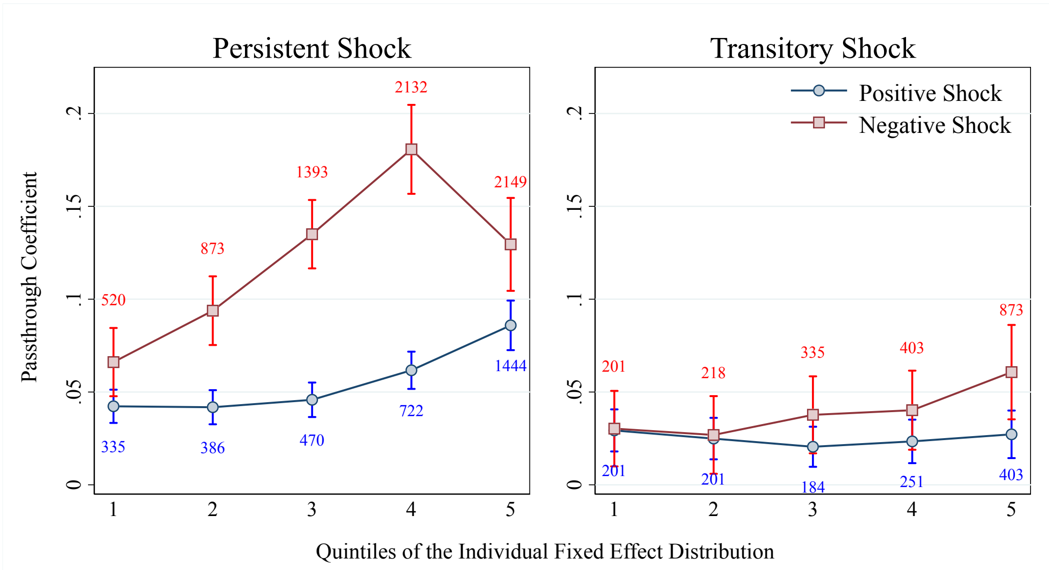
Note: Figure 3 shows the elasticity of hourly wages to a persistent (transitory) shock to firms productivity. In each plot the vertical lines show a 1% confidence interval. In each plot, the number above the lines represent the monetary value of a shock of one standard deviation. All monetary values are calculated relative to the average annual labor earnings within the corresponding group.

Figure 4 – Passthrough by Age Groups



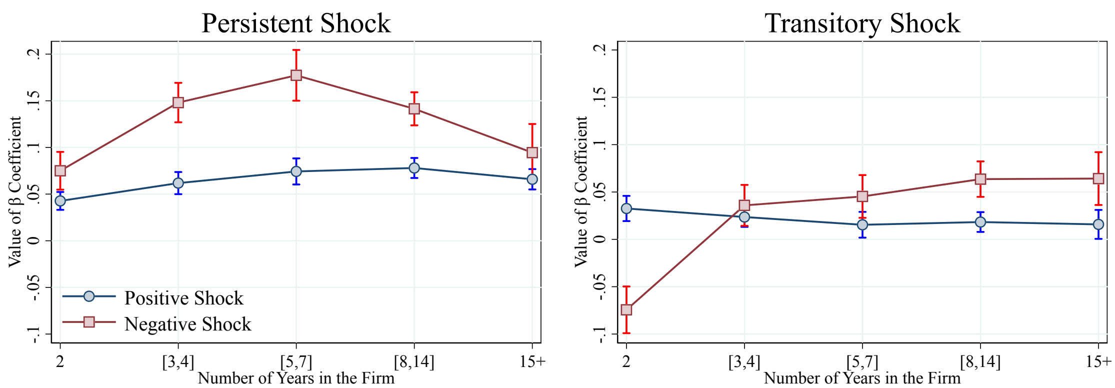
Note: Figure 4 shows the elasticity of hourly wages to a persistent (transitory) shock to firms productivity. In each plot the vertical lines show a 1% confidence interval. In each plot, the number above the lines represent the monetary value of a shock of one standard deviation. All monetary values are calculated relative to the average annual labor earnings within the corresponding group.

Figure 5 – Passthrough by Ability Groups



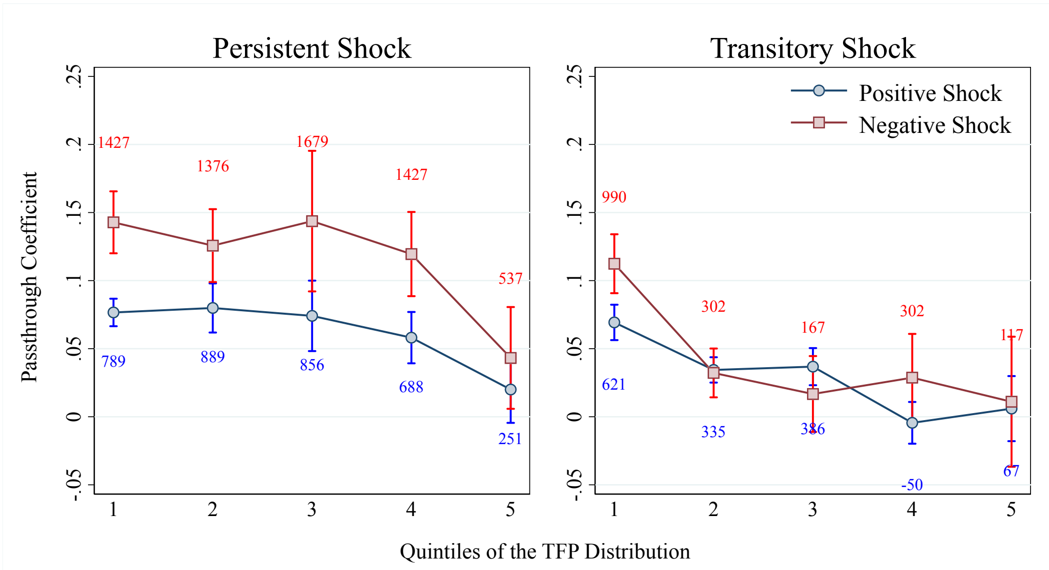
Note: Figure 5 shows the elasticity of hourly wages to a persistent (transitory) shock to firms productivity. In each plot the vertical lines show a 1% confidence interval. In each plot, the number above the lines represent the monetary value of a shock of one standard deviation. All monetary values are calculated relative to the average annual labor earnings within the corresponding group.

Figure 6 – Passthrough by Tenure Groups



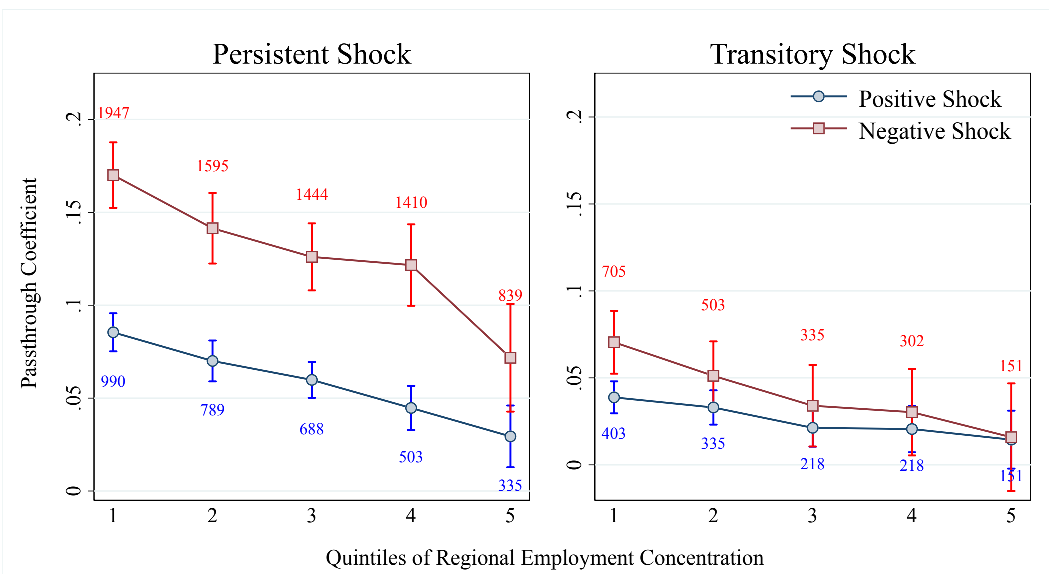
Note: Figure 6 shows the elasticity of hourly wages to a persistent (transitory) shock to firms productivity. In each plot the vertical lines show a 1% confidence interval. In each plot, the number above the lines represent the monetary value of a shock of one standard deviation. All monetary values are calculated relative to the average annual labor earnings within the corresponding group.

Figure 7 – Passthrough by Firms Productivity Groups



Note: Figure 7 shows the elasticity of hourly wages to a persistent (transitory) shock to firms productivity. In each plot the vertical lines show a 1% confidence interval. In each plot, the number above the lines represent the monetary value of a shock of one standard deviation. All monetary values are calculated relative to the average annual labor earnings within the corresponding group.

Figure 8 – Passthrough by Employment Share Groups



Note: Figure 8 shows the elasticity of hourly wages to a persistent (transitory) shock to firms productivity. In each plot the vertical lines show a 1% confidence interval. In each plot, the number above the lines represent the monetary value of a shock of one standard deviation. All monetary values are calculated relative to the average annual labor earnings within the corresponding group.

A Appendix

Figure A.1 – Positive and Negative Shocks Have Long-Lived Impact on Wages

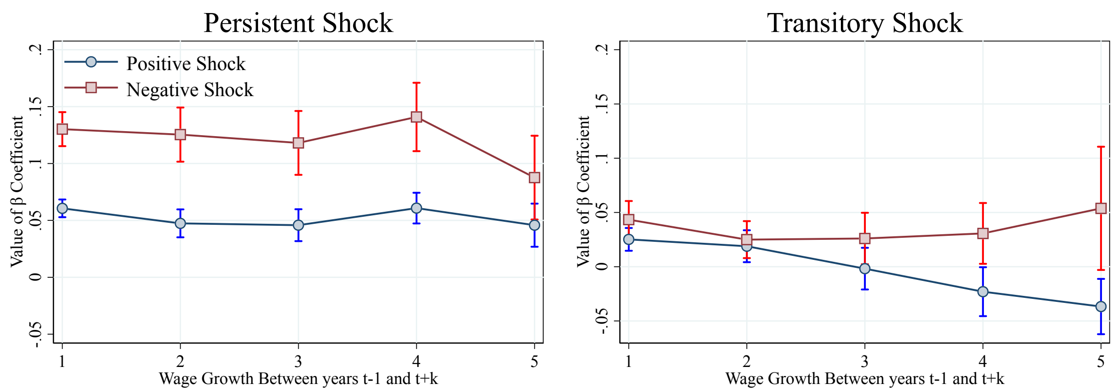


Figure A.2 – Positive and Negative Shocks Have Long-Lived Impact on Wages: Balanced Panel